

NAS  
NAE  
IOM

AD-A223 515

# On-Line Control of Metal Processing

AD-A223 515

National Materials Advisory Board  
Commission on Engineering and Technical Systems  
National Research Council

NATIONAL RESEARCH COUNCIL  
COMMISSION ON ENGINEERING AND TECHNICAL SYSTEMS

**NATIONAL MATERIALS ADVISORY BOARD**

The purpose of the National Materials Advisory Board  
is the advancement of materials science and engineering in the national interest.

**CHAIRMAN**

Dr. Bernard H. Kear  
Chairman, Dept. of Mechanics  
and Materials Science  
Dir., Center for Materials  
Synthesis  
College of Engineering  
Rutgers University  
P.O. Box 909  
Piscataway, NJ 08854

**PAST CHAIRMAN**

Dr. Arden L. Bement, Jr.  
Vice President, Technical  
Resources  
Science and Technology Dept.  
TRW, Inc.  
1900 Richmond Road  
Cleveland, OH 44124

**MEMBERS**

Dr. Norbert S. Baer  
Hagop Kevorkian Professor of  
Conservation  
New York University  
Conservation Center of the  
Institute of Fine Arts  
14 East 78th Street  
New York, NY 10021

Dr. Frank W. Crossman  
Assistant Director, Information  
Services  
Lockheed Missiles & Space  
Co., Inc  
Org. 19-66, Bldg. 102  
P.O. Box 3504  
Sunnyvale, CA 94088-3504

Mr. Edward J. Dulis  
President  
Crucible Research Center  
Crucible Materials Corporation  
P.O. Box 88  
Pittsburgh, PA 15230

Dr. James Economy  
Professor and Head of Materials  
Science  
University of Illinois  
1304 Green Street  
Urbana, IL 61801

Dr. Merton C. Flemings  
Professor and Chairman  
Department of Materials  
Science and Engineering  
Massachusetts Institute of  
Technology  
77 Massachusetts Avenue  
Cambridge, MA 02139

Dr. James A. Ford  
Vice President, Technology  
SELEE Corporation  
P.O. Box 747  
Hendersonville, NC 28739

Dr. John K. Hulm  
Chief Scientist  
Westinghouse Research  
Laboratories  
1310 Beulah Road  
Pittsburgh, PA 15235

Dr. Melvin F. Kanninen  
Institute Scientist  
Southwest Research Institute  
P.O. Drawer 28510  
San Antonio, TX 78284

Dr. Robert A. Laudise  
Director, Physical and  
Inorganic Chemistry Research  
Laboratory, Room 1A-264  
AT&T Bell Laboratories  
Murray Hill, NJ 07974

Dr. David L. Morrison  
President  
IIT Research Institute  
10 West 35th Street  
Chicago, IL 60616

Dr. Donald R. Paul  
Melvin H. Gertz Regents Chair  
in Chemical Engineering  
Director, Center for  
Polymer Research  
University of Texas  
Austin, TX 78712

Dr. Joseph L. Pentecost  
Professor  
School of Materials  
Engineering  
Georgia Institute of  
Technology  
Atlanta, GA 30332

Dr. John P. Riggs  
Vice President, R&D  
Research Division  
Managing Director, Mitchell  
Technical Center  
Hoechst Celanese Corp.  
86 Morris Avenue  
Summit, NJ 07901

Dr. Maxine L. Savitz  
Director  
Garrett Ceramic Components  
Division  
19800 South Van Ness Ave.  
Torrence, CA 90509

Dr. William P. Slichter  
AT&T Bell Laboratories  
(Retired)  
55 Van Doren Avenue  
Chatham, NJ 07928

Dr. Dale F. Stein  
President  
Michigan Technological  
University  
Houghton, MI 49931

Dr. John E. Tilton  
Coulter Professor  
Department of Mineral  
Economics  
Colorado School of Mines  
Golden, CO 80401

Mr. James R. Weir, Jr.  
Associate Director  
Metals & Ceramics Division  
Oak Ridge National Laboratory  
P.O. Box X  
Oak Ridge, TN 37830

Dr. Robert M. White  
Vice President, Research &  
Engineering  
Control Data Corporation  
8100 34th Avenue South  
Minneapolis, MN 55440

Dr. James C. Williams  
General Manager  
Materials Technology Laboratories  
General Electric Company  
1 Neumann Way  
Cincinnati, OH 45215-6301

**NMAB STAFF**

K.M. Zwilsky, Director  
S.M. Barkin, Assoc. Director  
Mary Brittain, Adm. Officer  
2101 Constitution Ave., NW  
Washington, DC 20418

# REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION <b>UNCLASSIFIED</b>			1b. RESTRICTIVE MARKINGS <b>NONE</b>		
2a. SECURITY CLASSIFICATION AUTHORITY ---			3. DISTRIBUTION/AVAILABILITY OF REPORT  <b>UNLIMITED</b>		
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE ---					
4. PERFORMING ORGANIZATION REPORT NUMBER(S) <b>NMAB-444</b>			5. MONITORING ORGANIZATION REPORT NUMBER(S) ---		
6a. NAME OF PERFORMING ORGANIZATION <b>NATIONAL MATERIALS ADVISORY BOARD</b>		6b. OFFICE SYMBOL (If applicable) <b>NMAB</b>	7a. NAME OF MONITORING ORGANIZATION <b>U.S. DEPARTMENT OF DEFENSE NATIONAL AERONAUTICS AND SPACE ADMINISTRATION</b>		
6c. ADDRESS (City, State, and ZIP Code) <b>2101 Constitution Ave. N.W. Washington, DC 20418</b>			7b. ADDRESS (City, State, and ZIP Code) <b>Washington, DC 20301</b>		
8a. NAME OF FUNDING/SPONSORING ORGANIZATION <b>See 7a</b>		8b. OFFICE SYMBOL (If applicable) <b>DOD/NASA</b>	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER <b>MDA 903-86-K-0220</b>		
8c. ADDRESS (City, State, and ZIP Code) <b>Washington, DC 20301</b>			10. SOURCE OF FUNDING NUMBERS		
			PROGRAM ELEMENT NO ---	PROJECT NO ---	TASK NO ---
					WORK UNIT ACCESSION NO ---
11. TITLE (Include Security Classification) <b>ON-LINE CONTROL OF METAL PROCESSING</b>					
12. PERSONAL AUTHOR(S) <b>NMAB Committee on On-Line Control of Metal Processing</b>					
13a. TYPE OF REPORT <b>FINAL</b>		13b. TIME COVERED FROM <b>5/86</b> TO <b>1/89</b>		14. DATE OF REPORT (Year, Month, Day) <b>February 1989</b>	
				15. PAGE COUNT <b>114</b>	
16. SUPPLEMENTARY NOTATION ---					
17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)		
FIELD	GROUP	SUB-GROUP			
---	---	---	Artificial intelligence		
---	---	---	On-line control		
---	---	---	Process control		
19. ABSTRACT (Continue on reverse if necessary and identify by block number) Efficient manufacturing requires modeling of the process so as to understand where controls need to be applied, sensors need to be installed, and a control strategy needs to be executed. This report examines these elements as they apply to metal processing. Process analysis leads to the development of a model that shows the points where controls should be applied. Controls may range from a single loop to sophisticated artificial intelligence. Sensors are used to measure process variables so that they can be controlled in real time in such a way as to attain microstructural, compositional, and geometrical goals. On-line process control has not been widely achieved in metallurgical industries. Casting, forging, and particulate production are examined and evaluated with regard to on-line processing, and the factors that limit progress in this area are discussed.					
20. DISTRIBUTION/AVAILABILITY OF ABSTRACT <input checked="" type="checkbox"/> UNCLASSIFIED/UNLIMITED <input type="checkbox"/> SAME AS RPT <input type="checkbox"/> DTIC USERS			21. ABSTRACT SECURITY CLASSIFICATION <b>UNCLASSIFIED</b>		
22a. NAME OF RESPONSIBLE INDIVIDUAL <b>JEROME PERSH</b>			22b. TELEPHONE (Include Area Code) <b>(202) 695-0005</b>		22c. OFFICE SYMBOL <b>OUSDR&amp;E/R&amp;AT/MST</b>

# **ON-LINE CONTROL OF METAL PROCESSING**

Report of the  
Committee on On-Line Control of Metal Processing

NATIONAL MATERIALS ADVISORY BOARD  
Commission on Engineering and Technical Systems  
National Research Council

NMAB-444  
National Academy Press  
1989

NOTICE: The project that is the subject of this report was approved by the Governing Board of the National Research Council, whose members are drawn from the councils of the National Academy of Sciences, the National Academy of Engineering, and the Institute of Medicine. The members of the committee responsible for the report were chosen for their special competences and with regard for appropriate balance.

This report has been reviewed by a group other than the authors according to procedures approved by a Report Review Committee consisting of members of the National Academy of Sciences, the National Academy of Engineering, and the Institute of Medicine.

The National Academy of Sciences is a private, nonprofit, self-perpetuating society of distinguished scholars engaged in scientific and engineering research, dedicated to the furtherance of science and technology and to their use for the general welfare. Upon the authority of the charter granted to it by the Congress in 1863, the Academy has a mandate that requires it to advise the federal government on scientific and technical matters. Dr. Frank Press is president of the National Academy of Sciences.

The National Academy of Engineering was established in 1964, under the charter of the National Academy of Sciences, as a parallel organization of outstanding engineers. It is autonomous in its administration and in the selection of its members, sharing with the National Academy of Sciences the responsibility for advising the federal government. The National Academy of Engineering also sponsors engineering programs aimed at meeting national needs, encourages education and research, and recognizes the superior achievements of engineers. Dr. Robert M. White is president of the National Academy of Engineering.

The Institute of Medicine was established in 1970 by the National Academy of Sciences to secure the services of eminent members of appropriate professions in the examination of policy matters pertaining to the health of the public. The Institute acts under the responsibility given to the National Academy of Sciences by its congressional charter to be an advisor to the federal government and, upon its own initiative, to identify issues of medical care, research, and education. Dr. Samuel O. Thier is president of the Institute of Medicine.

The National Research Council was organized by the National Academy of Sciences in 1916 to associate the broad community of science and technology with the Academy's purposes of furthering knowledge and advising the federal government. Functioning in accordance with general policies determined by the Academy, the Council has become the principal operating agency of both the National Academy of Sciences and the National Academy of Engineering in providing services to the government, the public, and the scientific and engineering communities. The Council is administered jointly by both Academies and the Institute of Medicine. Dr. Frank Press and Dr. Robert M. White are chairman and vice chairman, respectively, of the National Research Council.

-----  
This study by the National Materials Advisory Board was conducted under Contract No. MDA 903-86-K-0220 with the Department of Defense and the National Aeronautics and Space Administration.

This report is available from the Defense Technical Information Center, Cameron Station, Alexandria, VA 22312.

Printed in the United States of America

# **ABSTRACT**

Efficient manufacturing requires modeling of the process so as to understand where controls need to be applied, sensors need to be installed, and a control strategy needs to be executed. This report examines these elements as they apply to metal processing. Process analysis leads to the development of a model that shows the points where controls should be applied. Controls may range from a single loop to sophisticated artificial intelligence. Sensors are used to measure process variables so that they can be controlled in real time in such a way as to attain microstructural, compositional, and geometrical goals. On-line process control has not been widely achieved in metallurgical industries. Casting, forging, and particulate production are examined and evaluated with regard to on-line processing, and the factors that limit progress in this area are discussed.



<b>Accession For</b>	
NTIS GRA&I	<input checked="" type="checkbox"/>
DTIC TAB	<input type="checkbox"/>
Unannounced	<input type="checkbox"/>
Justification	
By	
Distribution/	
Availability Codes	
Dist	Avail and/or Special
A-1	

## COMMITTEE ON ON-LINE CONTROL OF METAL PROCESSING

### Chairman

DIRAN APELIAN, Howmet Professor of Materials Engineering and Associate Dean,  
College of Engineering, Drexel University, Philadelphia, Pennsylvania

### Members

CHARLES E. ECKERT, Sensor Technical Specialist, Alcoa Technical Laboratories,  
Aluminum Company of America, Alcoa Center, Pennsylvania

LIONEL C. KIMERLING, Head, Materials Physics Research Department, AT&T Bell  
Laboratories, Murray Hill, New Jersey

HARRIS MARCUS, H. L. Kent, Jr., Professor of Mechanical Engineering,  
Department of Mechanical Engineering, University of Texas, Austin

DONALD R. SADOWAY, Associate Professor of Materials Engineering, Department of  
Materials Science and Engineering, Massachusetts Institute of Technology,  
Cambridge

ROBERT A. SPRAGUE, Manager, Materials Engineering and Process Laboratory,  
General Electric Company, Lynn, Massachusetts

HAYDN N. G. WADLEY, Professor of Materials Science and Mechanical/Aeronautical  
Engineering, University of Virginia, Charlottesville (formerly Group  
Leader, National Institute of Standards and Technology)

### Liaison Representatives

JEROME PERSH, Staff Specialist, Materials and Structures, Office of Deputy  
Under Secretary of Defense for R&E (ET), Department of Defense, Washington,  
D.C.

HAROLD GEGEL, Director, Processing Science Division, Universal Energy Systems,  
Inc., Dayton, Ohio (formerly Air Force Wright Aeronautical Laboratory,  
Wright-Patterson Air Force Base, Ohio)

PHILLIP PARRISH, Defense Advanced Research Projects Agency, Department of  
Defense, Arlington, Virginia

RALPH ADLER, Department of the Army, Materials Technology Laboratory,  
Watertown, Massachusetts

ROBERT J. GOTTSCHALL, Program Manager, Division of Materials Science,  
Department of Energy, Washington, D.C.

NMAB STAFF

JOSEPH R. LANE, Senior Program Officer

JUDITH AMRI, Senior Secretary



## CONTENTS

	<u>Page</u>
Chapter 1 EXECUTIVE SUMMARY	1
Modeling	2
Sensing	3
Controlling	5
Other Needs and Barriers	6
Chapter 2 CONCEPTS AND PRINCIPLES	9
Process Understanding	10
Types of Process Control	13
Sensing for On-Line Control	14
References	17
Chapter 3 PROCESS UNDERSTANDING	19
Process Variables	19
Modeling Approaches	21
Uses of Process Models	22
VLSI: A Model for Materials Process Control	23
Pitfalls	24
Process Model Research	25
Summary	27
Bibliography	28
Chapter 4 CONTROLS	29
Raw Materials and Products	29
Improvement Needed in Metals Processing Control	29
Discrete Loop Process Control	30
Feed-Forward Control	34
Intelligent Control	35
Flexible Manufacturing Systems and Hierarchical Control	37
Artificial Intelligence	40
References	40
Chapter 5 SENSING	43
Fundamental Quantities	43
Principles of Measurement	44
Sensor-Media Interaction Models	52

	<u>Page</u>
Emerging Sensors	53
Inverse Problems	68
Summary and Future Needs	69
References	70
Chapter 6 IMPLEMENTATION OF ON-LINE PROCESS CONTROL	73
Traditional Approach	73
Future Casting Process	76
Process Controls in Forging	79
Particulate Processes	82
Further Needs	84
Summary	96
References	96
Chapter 7 FUTURE NEEDS AND BARRIERS	97
Appendix BIOGRAPHICAL SKETCHES OF COMMITTEE MEMBERS	101

#### TABLES AND FIGURES

Table 2-1	Metal processes	9
Table 2-2	Factors in intelligent processing of materials	16
Table 5-1	Six groups of signals with examples	45
Table 5-2	Transducers and effects	46
Table 5-3	Welding defect detection and acoustic emission	68
Table 6-1	Implementation cost	95
Table 6-2	Relative manufacturing cost	96
Figure 1-1	A simple process control loop	6
Figure 2-1	The physical components and functions of a materials fabrication system	11
Figure 2-2	Cause-and-effect diagram of deformation in the heat treatment of metal parts	11
Figure 2-3	Modeling of the materials fabrication system	12
Figure 2-4	General form of a flexible manufacturing system	15
Figure 2-5	Functional elements of a flexible manufacturing system	15
Figure 2-6	Intelligent processing of materials	16
Figure 3-1	Activities involved in manufacturing	20
Figure 3-2	Choices in process design	21
Figure 3-3	Silicon processing for VLSI: value added	23
Figure 3-4	Defect criteria map	26
Figure 4-1	A continuous ingot casting process with three discrete control loops	32
Figure 4-2	Controller incorporating process model	36
Figure 4-3	Real-time molten metal chemistry control	37
Figure 4-4	Conventional metal treatment system	38
Figure 4-5	The flexible metal treatment system	39

	<u>Page</u>
Figure 5-1 Physical and chemical effects for input transducers	46
Figure 5-2 Three-dimensional transducer diagram showing the five possible modulating input transducers based on photoconductance, piezoresistance, thermoresistance, magnetoresistance, and electrolytic conductance effects	47
Figure 5-3 The electromagnetic spectrum	48
Figure 5-4 Density of modes $D(\omega)$ versus $\omega$	48
Figure 5-5 Blackbody curves for different temperatures showing the displacement of the maximum according to Wien's law	49
Figure 5-6 Scale of microstructure and associated NDE tools	50
Figure 5-7 Comparison of various analytical methods	51
Figure 5-8 Schematic illustration of surface defect sensor	55
Figure 5-9 Schematic illustration of the laser chemical composition probe being developed for liquid metal analysis	57
Figure 5-10 Dependence of Rayleigh wave velocity on wavelength ( $\lambda$ )	57
Figure 5-11 Dependence of longitudinal ultrasonic velocity upon temperature for AISI 304 stainless steel	59
Figure 5-12 Schematic diagram of ultrasonic internal temperature sensor utilizing laser generation and EMAT detection	60
Figure 5-13 The internal temperature distributions reconstructed from noncontact ultrasonic measurements compared with embedded thermocouple measurements (circles) for AISI 304 stainless steel	61
Figure 5-14 Proposed use of electromagnetic sensor for measuring the temperature of aluminum rod during extrusion processing	62
Figure 5-15 Schematic diagram illustrating the method of measurement of impedance	63
Figure 5-16 Impedance plot of measured test data on an aluminum rod 1 in. in diameter	64
Figure 5-17 Acoustic emission signals typically detected during resistance spot welding	66
Figure 6-1 New part start-up schedule	75
Figure 6-2 Incremental implementation of computer-aided technology.	77
Figure 6-3 Computer integrated casting	78
Figure 6-4 Closed-loop forging process	80
Figure 6-5 Schematic representation of metal-processing system from physical-systems-modeling viewpoint	81
Figure 6-6 A commercial alumina refinery flow diagram	83
Figure 6-7 Information flow	85
Figure 6-8 Machine tool monitoring system	88
Figure 6-9 Basic machine-tool monitoring technique	89
Figure 6-10 Three common normal cutting signal artifacts	89
Figure 6-11 Two common types of tool break signatures	90

## Chapter 1

### EXECUTIVE SUMMARY

A technological revolution is in progress throughout the industrial world that is influencing the entire manufacturing process. Because a nation's productivity is directly related to its ability to "intelligently" manufacture, this revolution has led to intense global competition among manufacturing nations striving to improve their economic positions. At issue, then, is how to improve the U.S. manufacturing position in this international struggle.

The emergence of advanced sensors coupled with process modeling, artificial intelligence, and expert systems has created the possibility of new approaches to materials processing. It has become feasible in some cases to fully implement computer-integrated manufacturing where process, quality and product control, and flexible manufacturing technologies are merged into a single, plant-wide, flexible manufacturing system, with enhanced productivity and product consistency and substantially reduced costs.

By comparison, marginal improvements in controlling metal processing will not provide needed economies of production or desired uniform quality. This is particularly true of batch processes, which are typical of foundries, forge shops, and other metallurgical operations. In addition, the need for tighter limits on the structure and properties of some products (semiconductors, for example) in items such as military hardware is forcing closer attention to process control. It is becoming evident that some materials (advanced semiconductors such as mercury-cadmium telluride) will be producible in desired sizes and quality only under completely automatic control.

There are several good reasons why advances in control of metal processing have lagged, besides the obvious expense of re-equipping factories. To control a process, it is necessary to thoroughly understand the process so as to appreciate where control should be applied, to be able to sense significant parameters, and to comprehend the control needs so as to implement an appropriate system. Capabilities in all three areas are limited. A revolution in some metallurgical operations, such as continuous (not batch) processing, requires on-line control. But advances primarily in understanding, as well as in equipment, are needed first. There is a great need to systemize and automate the decision-making

process in manufacturing systems. Much development activity could be justified on the expectation that better quality and lower costs will result. However, it must be appreciated that, although benefits might be great, the risks are significant, and a long-term effort will be required.

The intent of this study is to define and examine methodologies to establish on-line closed-loop control of metals processing during the manufacturing cycle. The committee has addressed this task by analyzing the various integral components of several model systems. The framework for controlling manufacturing systems is based on relevant concepts of operations research and decision theory as well as on insights gained from practical experience. Thus the knowledge base is made up of rules, assertions, precise models, and empirical know-how. In complex and complicated manufacturing processing cycles, a systems approach needs to be adopted to take into account the interactions between the system components.

The three principal components of an automated materials process control system are the process model, sensors, and control:

- A model of the process provides an understanding and a relationship of the independent and dependent variables.
- Sensors indicate and provide on-line information--real-time feedback--regarding critical and significant parameters as dictated by the model.
- A control function maintains quality assurance in the manufacturing process.

## MODELING

Process modeling is the foundation of process design and implementation. The ideal process model begins with specification of starting materials and ends with structure and composition to permit the prediction of final properties. The full implementation of process modeling in the design and control of metal processing is at least a decade away. Some models can be approximated with good estimates and experience; some may never exist. Current approaches to process design and implementation are not always useful because of a lack of fundamental knowledge and commercially available equipment. A new approach is needed to ensure that on-line control does not degenerate into merely a proliferation of sensor installations, resulting in complexity and fault intolerance rather than simplicity and quality.

Control can be enhanced by use of artificial intelligence (AI). It is important to distinguish between AI and conventional numerical processing. Although numerical processing methods and hardware have developed to prodigious capabilities in recent years, the basic element of the method is procedural and the output is predictable. Specific facts are provided for the system that are subsequently used to build an explicitly structured rigid data base. This data base is accessed, and the information is used in a logical sequence of instructions that

progresses toward the solution. Conversely, AI does not derive a predictable, predetermined output from a fact-based data base; rather, stored knowledge and information is processed by an inference mechanism to yield a rational conclusion. AI can make a significant impact on process control as an enabling technology.

Certain metals processing control applications exhibit system dynamics or sensor limitations that necessitate both monitoring of the principal process variable and the use of models. A more complex controller that relies on additional input variables and incorporates a model of the process can be successfully used in those cases where physical limitations restrict sampling frequency or impose transport delays.

The committee reached the following conclusions pertaining to modeling:

- A new process design methodology needs to be developed that integrates fundamental understanding with numerical methods to simplify sensing and control. Such a methodology must clearly identify the relationship between control variables and performance margin and should establish the control criteria for process selection. The process design methodology also needs to be constrained by a figure-of-merit approach to process durability.

- Much fundamental research is needed in process understanding and the development of relevant process models, particularly in processing far from equilibrium involving nonlinear, dynamic responses to system fluctuations. In addition, fundamental research is needed in the simultaneous consideration of gradients in time with gradients in space.

- Process models will lead to process understanding only if the models developed utilize accurate materials data. Unfortunately, the data base (viscosity, thermophysical properties, heat transfer coefficients, etc.) is nonexistent or not reliable. A cooperative joint industry-university-National Institute of Standards and Technology program funded by the federal government (DOD, NSF, DOE) to measure and collect the required model parameters at industrial sites is needed. Such data would have a significant impact.

## SENSING

A sensor is a device that detects or measures some physical or chemical quantity and converts the measurement from one signal domain to another, typically electrical. The electrical signal is converted into a form that can either (a) be perceived by human senses (visually or aurally), in which case the device is termed a display, or (b) cause some physical change in the process (e.g., open a valve or throw a switch), in which case the device is termed an actuator. A model is used to formulate a control law, which in turn is the basis by which the sensed signal is interpreted, resulting in driving an actuator.

Like other materials, metals should be considered "bundles of properties." These properties determine the performance limits of the material and often the value of manufactured products. However, materials science teaches that there is a direct correlation between the properties of a metal and its structure. It is the role of sensors to measure process variables so that they can be controlled in real time to attain microstructural and compositional goals and thereby ensure compliance with performance specifications. This is an essential aspect of on-line process control. However, the sensing and control of process variables alone will not guarantee a singular microstructure. Variability in raw materials and other stochastic phenomena cause variations in microstructure distributions and wide ranges in properties. To combat this, sensors are needed to directly probe some property that will relate to the subsequent microstructure. This represents a significant challenge to measurement science, given the often extreme process environment and the need to not interfere with the process itself.

Compliance with performance specifications can be assured by measuring indirect or derived quantities such as eddy currents and electrical conductivity (electrical properties), magnetometry and Barkhausen noise (magnetic properties), ultrasound (elastic properties), and optical absorption and scattering (optical properties). Other characteristics that can be taken as indicators of quality include dielectric and thermal properties. In all cases, however, the sensors are bound by the laws of physics as applied to metallic matter.

The first requirement of a sensor is that it not perturb the subject under investigation. Some processes do not lend themselves to this form of monitoring, and alternatives must be sought with the intention of causing the least disturbance. A second consideration in choosing or designing a sensor is the time needed to make and perhaps manipulate a measurement as compared to the response time of the process. A third concern is that sensors for metal processing in many cases are employed in hostile environments--high temperatures, extreme chemistries (highly oxidizing, highly reducing, corrosive), electromagnetic interference, etc. Sensors for these environments must be stable, robust, and reliable.

The committee reached these conclusions regarding sensors:

- The lack of adequate sensors is an important impediment to the implementation of new materials processing strategies. Even though there are no major technological roadblocks to the development of metal processing sensors, the pace of development has been slow. One reason may be the application-specific nature of many sensors. Potential markets for sensors are often small, whereas their development costs and risks are great. Collaborative programs in the metals industry may be one mechanism to encourage sensor development. More extensive government funding of generic measurement sciences is urgently needed, given the impact a generation of sensors could have on the international competitiveness of the domestic metals industry.

- Many of the sensor technologies of importance are only just emerging from research laboratories. Thus, the technical expertise for sensor development often does not reside in either the research organ-

izations of the materials processing community or the vendor companies supplying control instrumentation. Furthermore, those researchers who are conversant with emerging sensor technologies are often unaware of research opportunities in materials processing. There is a need to improve the dialogue and technology transfer between the materials processing community and those involved in applicable measurement science. Consideration should be given to including sensor-related topics in the curricula of university materials science courses.

- Basic research on the generic aspects of sensor technology needs to be encouraged in industry, government, and universities. Remote sensing capabilities need to be enhanced, new signal processing and analysis techniques await development, and sensor-media interaction modeling opportunities abound. Stronger federal support for these aspects of measurement science would do much to enhance the technology pool from which the materials processing community will draw its future sensor development efforts.

## CONTROLLING

The implementation of on-line process control (OLPC) is the final and most difficult step toward true process automation. Proper sensor location, control systems durability, data bases, and accessibility are mandatory to success.

The basic element of all process control is the control loop. This loop, consisting of a sensor, controller, and operator, regulates a discrete operation in a completely predetermined manner. Regulation is accomplished by adjusting the input variables from the process to the manipulated variables through a transfer function. Since the transfer function is a fixed relationship, control will always occur within this context. A discrete process control loop is shown in Figure 1-1.

Intelligent controllers and sophisticated sensors have significantly enhanced metal processing during the past decade. Early examples of such controllers were essentially multichannel solid-state switching devices with an operating system based on relay logic that was interfaced with a supervisory computer. As central processing unit power and memory size increased, the utility role of the computer was extended to event scheduling, process operating practice storage, and real-time data acquisition. Within the past 5 years, enhanced hardware has emerged that can fully control complex processes such as rolling mills, continuous casters, and primary metals refining units.

The majority of sensors needed in forge process controls are relatively inexpensive. The key, as with other processes, is to understand where these need to be used and the selection of controlling process parameters that will ensure the required part quality along with specific mechanical and physical characteristics. Sensors are required for controlling or monitoring time, pressure, temperature (contact or noncontact type), die or press velocity, die deflection, and dimensions.



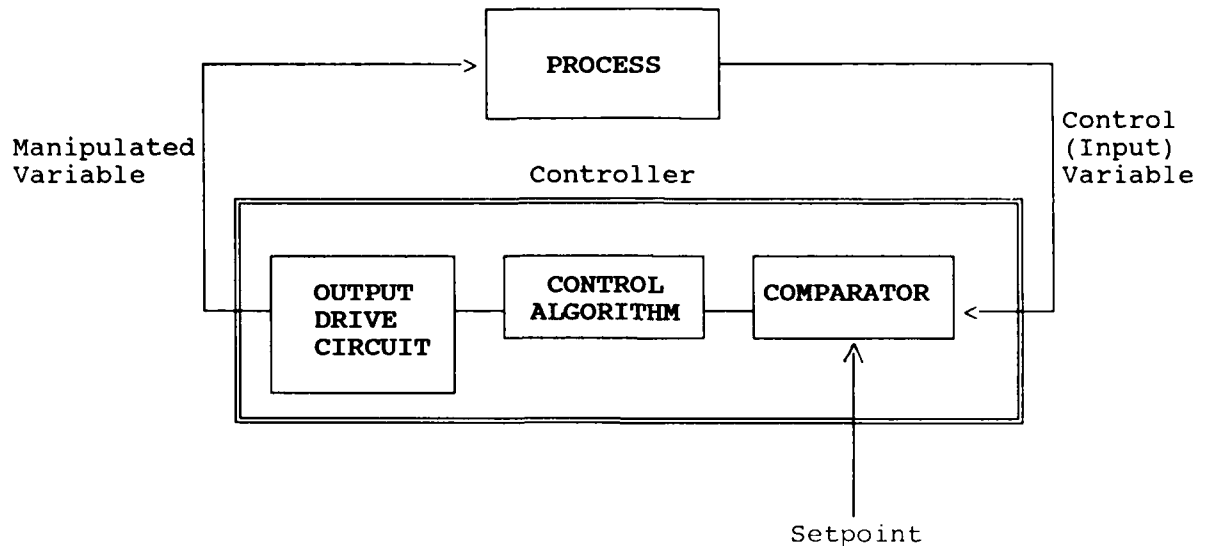


FIGURE 1-1 A simple process control loop.

The committee concluded the following regarding process controls:

- On-line connotes that the response is immediate. There are many metals processing operations where the computational time needed to be "on-line controlled" requires large computers. Here, the cost becomes prohibitive. Special-purpose computers, which are designed for specific computational formalisms and enhanced speed, are needed.
- The cost and risk barriers to implementation of OLPC--particularly when coupled with a new materials technology such as high-temperature composites--are major obstacles. The potential investor is faced not only with the capital risk of successfully meeting the cost objectives of an OLPC venture but also with the risk of product need and/or acceptability even if the plant product objectives are met. A prime requirement is the combination of equipment and product design and close coordination among equipment manufacturer, product producer, and product user. Beyond this, government stimulus, perhaps in the forms of prototype facilities subsidy, product evaluation support, and tolerance for the learning-curve cost burden inherent in early production, may be necessary to establish initial capability, especially in cases where advanced processing concepts are combined with revolutionary materials compositions and forms.

#### OTHER NEEDS AND BARRIERS

##### Data Bases

A principal technical barrier to OLPC for metals processing is data bases. In most cases they do not exist in either a complete or usable format. Because of the nature of investment casting, geometric complexity is essentially limitless; it reaches its fullest expression with turbine blade designs. This ultimately requires an extensive data

with turbine blade designs. This ultimately requires an extensive data base that fully describes the necessary features of the casting. Since the aircraft engine industry has a similar interest in using this geometry data base for design and manufacture of the engine, the task is to ensure that, in the design stage, sufficient information is produced to satisfy the needs of the investment foundries and that the format is usable and the pertinent data are easily retrievable.

### System Integration

The system integration required for OLPC begins with management and operator acceptance of change. Line management must accept loss of the direct control and decision-making functions built into the system. The operators and their bargaining units must accept the work scope flexibility that accompanies OLPC. Issues such as multifunctional job codes and nontraditional work schedules must be accepted if the benefits of OLPC systems are to be realized. A key question is whether the market will be satisfied by existing producers, by new ventures in the United States, or by foreign producers.

### Economic Concerns

The start-up of an OLPC facility often entails high initial costs. These include return on investment (reasonable profitability and allowance for depreciation costs); unpredicted and unfavorable associated costs (low initial volume, unplanned technical problems); and certification barriers, particularly in DOD systems. Here a structured procurement system does not permit initial cost disadvantage for later cost superiority relative to proven state-of-the-art technology level, and a product quality assurance plan demands redundant or enhanced quality assurance requirements on new or revised processes. Thus, economic considerations may override technical barriers. To achieve the full benefits of OLPC, cooperative agreements between the user (DOD), the producer (aircraft engine prime contractors), and subcontractors (casting vendors) may be necessary.

In conclusion, the future feasibility of process control systems is frequently perceived to be limited by peripheral components such as sensors. This is especially so for materials processing. However, there is also a pressing need for solution of the primary problem: development of process models capable of interpreting sensor data and restructuring a process trajectory to bring the process back within bounds. Other obstacles, such as compiling the required data bases and integrating system operations and management, are not insurmountable but will demand close attention. In the long run, economic considerations may overshadow the technical problems.

## Chapter 2

### CONCEPTS AND PRINCIPLES

Successful implementation of on-line control of metal processing involves full integration of design, procurement, and control of incoming components, manufacture, assembly, handling, packaging, and distribution. In this report the focus is on metals processing.

There are three primary concerns if on-line control of metal processing is to be successful. These are (a) definitive understanding of the processes, (b) availability of models for controlling the processes, and (c) sensors that can interrogate the processes in a manner that allows for process control. Some of the metal processes to be considered in terms of defining ultimate

TABLE 2-1 Metal Processes

---

#### Primary and Chemistry

- Extraction; smelting; refining

#### Shape Changes (Solid State)

- Forging
- Machining; stamping; forming
- Consolidation; powder formation
- Extrusion; swaging
- Rolling
- Drawing

#### Shape Changes (Liquid/Solid Transformation)

- Joining; welding
- Solidification; casting

#### Surface Modification

- Coating; plating; implantation
-

capabilities are given in Table 2-1. It must be pointed out that, during these processes, microstructural changes occur either deliberately or as a result of shape processing. Intrinsic to process control is a clear definition of the properties required at the end of individual steps and the relation of the intermediate properties to those specified for the material when the total processing is completed. In fact, only in the light of a definition of the properties and the processes is it possible to define the parameters that can be monitored for on-line control.

## PROCESS UNDERSTANDING

Process understanding makes possible three primary activities: (a) the definition of true process variables, (b) the choice of modeling approaches, and (c) the implementation of process models in on-line metals processing control.

It is clear that an accurate description of the process, as well as a good understanding of the system, is a prerequisite for optimizing the manufacturing cycle. There are three distinct ways that one can address the manufacturing system:

- One approach is to consider the physical system--that is, to consider the various physical components in the work station associated with the manufacturing system. Figure 2-1 shows the physical components and functions of a materials fabrication system.

- Another approach is to consider the manufacturing system as a cause-and-effect system, where the effects are the manufacturing system outputs and the causes are parameters of the various physical components. A cause-and-effect diagram, or Ishikawa diagram, is shown in Figure 2-2.

- A third approach is to consider the manufacturing system as a parametric model (Figure 2-3). Here the output variables relate to the manufactured part and the input variables include feedstock, work station conditions, operating factors, and controlling factors.

The process variables fall into seven generic classifications: temperature, pressure, chemical composition, size or spatial distribution of phases (microstructure), chemical gradient or depth distribution, temporal distributions, and physical properties (also temporal varying). Fundamental understanding as the basis of the choice and implementation of process variables proceeds as follows. The process is initially designed for control. From the designed process, the critical process steps are chosen for monitoring. The ultimate desired properties are chosen for any end-point monitoring.

For this process understanding of the appropriate variables to be used in on-line metal processing controls, sensors of the appropriate sensitivity, bandwidth, and ruggedness must be available. It is important that the sensors be defined in terms of the very limits of potential detectability of the defined parameter. This potential detectability is in terms of what sensors are available and in terms of what can potentially become available. If adequate sensors to measure the defined parameters are available, it

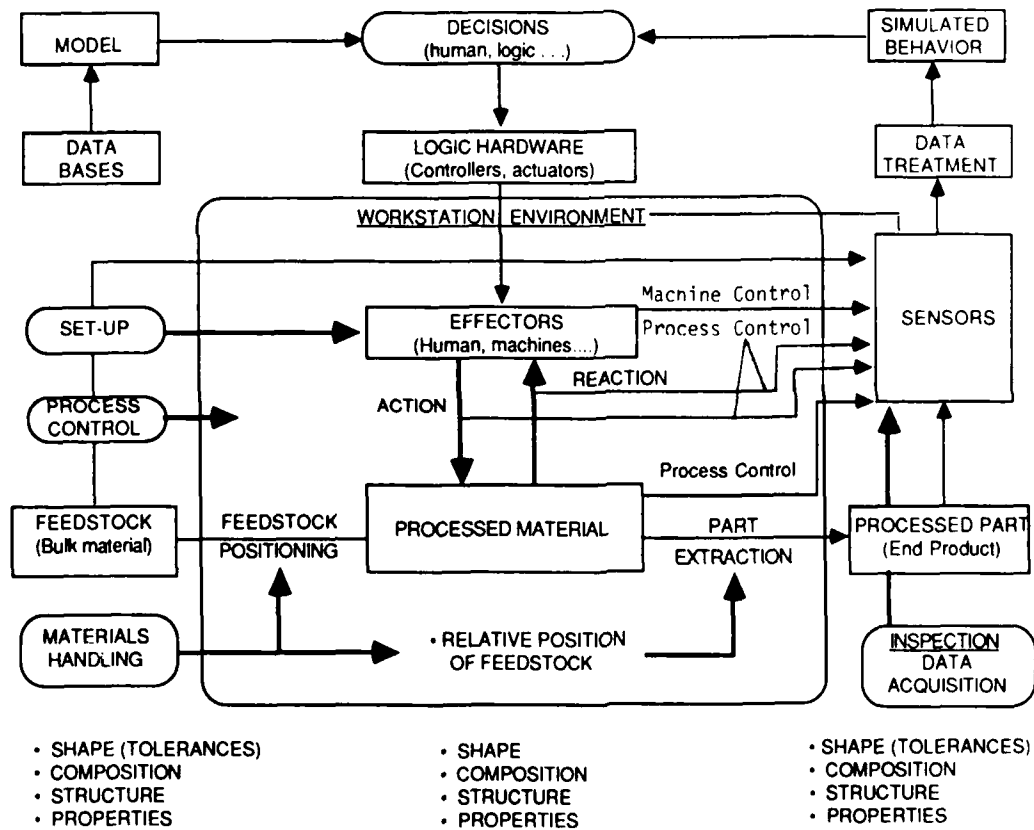


FIGURE 2-1 The physical components and functions of a materials fabrication system.

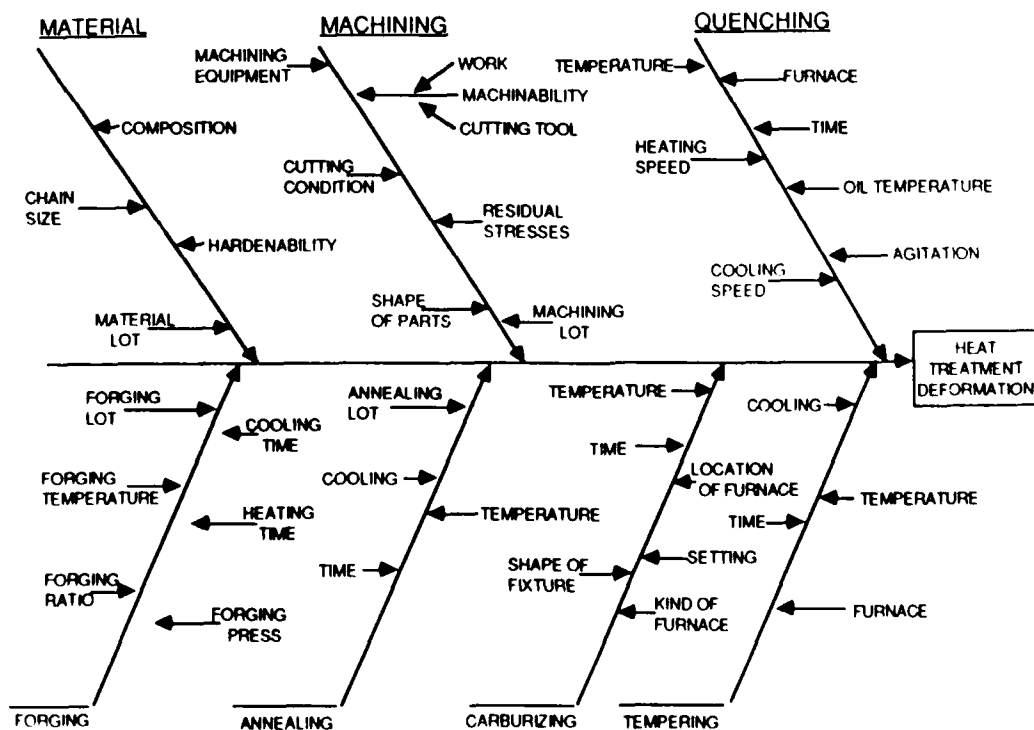


FIGURE 2-2 Cause-and-effect diagram of deformation in the heat-treatment of metal parts.

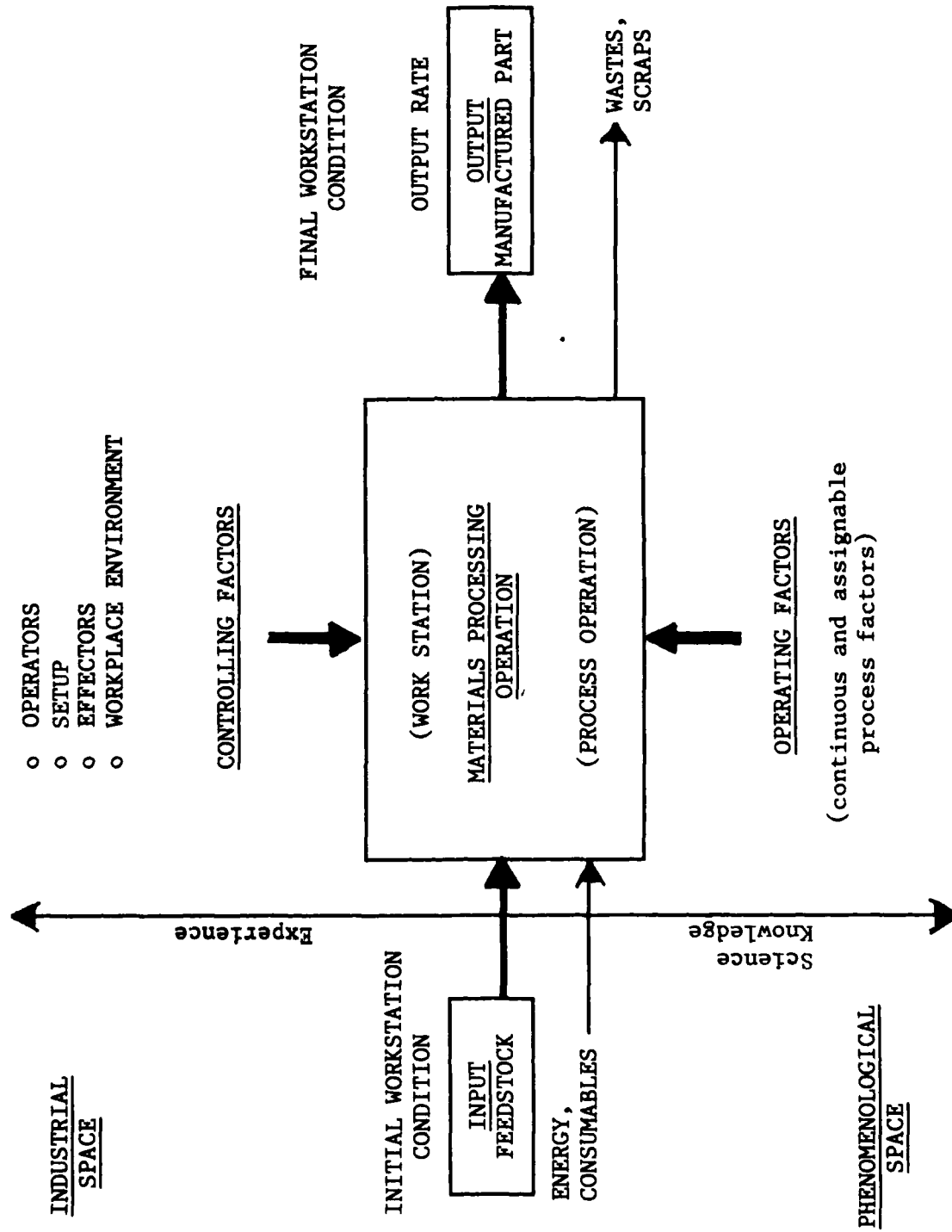


FIGURE 2-3 Modeling of the materials fabrication system (Fabrication Operation).

becomes necessary to redefine the process for control so appropriate parameters that can be reliably monitored can be established. The ultimate process would involve sensors that can induce a self-regulating process so that any change from the desired result would lead the process back automatically to the desired processing path. Chapter 3 describes, in terms of modeling approaches and their applicability to the processing, conditions where on-line metal processing control can be effective.

## TYPES OF PROCESS CONTROL

Control is management of the process to achieve end-product specifications with regard to shape and methodology. The control theories that are applicable vary widely but can be reduced to four distinct approaches. These are (a) feedback control, (b) feed-forward control, (c) intelligent control, and (d) artificial intelligence.

### Feedback Control

Feedback control is the approach most commonly used in manufacturing. A measured parameter is outside some control tolerance level, and the control system requests a predefined modification to the process, such as a change in power to control the temperature.

### Feed-Forward Control

Feed-forward control, used in flexible manufacturing systems (FMS), involves the methods associated with a feedback control system but also takes the control information and feeds it forward to the next step in the process. This then allows the subsequent processes to be modified to accommodate the measured deviations from the desired state. In both the feedback and feed-forward control schemes, the responses are predetermined by some control algorithm.

### Intelligent Control

The output of an "intelligent" control system is not based solely on the input from the sensors but is modeled, as, for example, in the use of adaptive control. This approach to control can be defined in terms of three cases. The first is when the time constant associated with the sampling is greater than the time constant of the system or process; this limits the ability to do modeling on a real-time basis. The second case occurs when the sampling time is less than the system or process time; this allows not only the use of real-time control but also the adjustment of the operating parameters according to some in-line model to handle transients within the process. The third case involves the use of multiple sensor information in the model. This allows integration of the processing information into a decision-making condition.

### Hierarchical Control

Within the concept of intelligent control is hierarchical control, where there is a multiple control system for a sequence of operations that makes up the processing. Each of the subprocesses has its own control system, but all of the controls are supervised by a larger computer that integrates the input

to the control models and defines the control output. Flexible manufacturing systems very often will also apply this approach. An example is given in Figures 2-4 and 2-5.

### Artificial Intelligence

This report views artificial intelligence (AI) in the context of expert systems\*. In this approach the expert information is incorporated into a control system where there is active control of a process, which is modified based on experience and the multiple input from the sensors. This approach is shown in Figure 2-6. The heuristic approach allows the control system to evaluate the incoming sensor data and make judgments based on prior knowledge, but changes in the processing parameters are not preordained. The factors that influence the applicability of AI to on-line processing of metals are shown in Table 2-2. The extensive interactions among process understanding, the control theories just described here, and the sensors are discussed in detail in Chapter 4.

### SENSING FOR ON-LINE CONTROL

In the foregoing description of basic understanding of both the processing and the control theories used in the processing, an underlying requirement has been assumed. This is that the appropriate sensors to determine the control parameters with sufficient accuracy are available. This section discusses some of the important factors in sensing that must be integrated into the on-line control of metal processing for it to be successful. It is the role of the sensor to measure process variables that can be controlled in real time in such a way as to attain compositional, microstructural, and dimensional goals that ensure compliance with performance specifications. The ability to sense by itself is of no value unless the sensed information can be incorporated into a control system in a manner that is meaningful for the processing. The process variables that can be sensed were described earlier. Sensing all the possible variables in a process is usual and adds to the confusion of the control process. What should be sensed are only those parameters that will assist in the control process.

Sensors are defined as devices that detect and measure some physical or chemical quantity and produce a signal, usually electrical, that is proportional in some manner to the condition of the system. There is a wide range of sensors already existing that are the basis for the field of nondestructive testing. Using the output of the sensors as the input signal for the control system is the primary goal in on-line control of metal processing. Traditional sensors were generally very limited in response

---

\*An expert system is defined as a computer program that contains both declarative knowledge (facts about objects, events, and situations) and procedural knowledge (information about courses of action) to imitate the reasoning processes of human experts in a particular domain. There are two types of expert systems: rule-based and model-based. The components of an expert system are a knowledge base, an inference engine, and a user interface (Henry C. Mishkoff, Understanding Artificial Intelligence, Texas Instruments, Dallas, Texas).



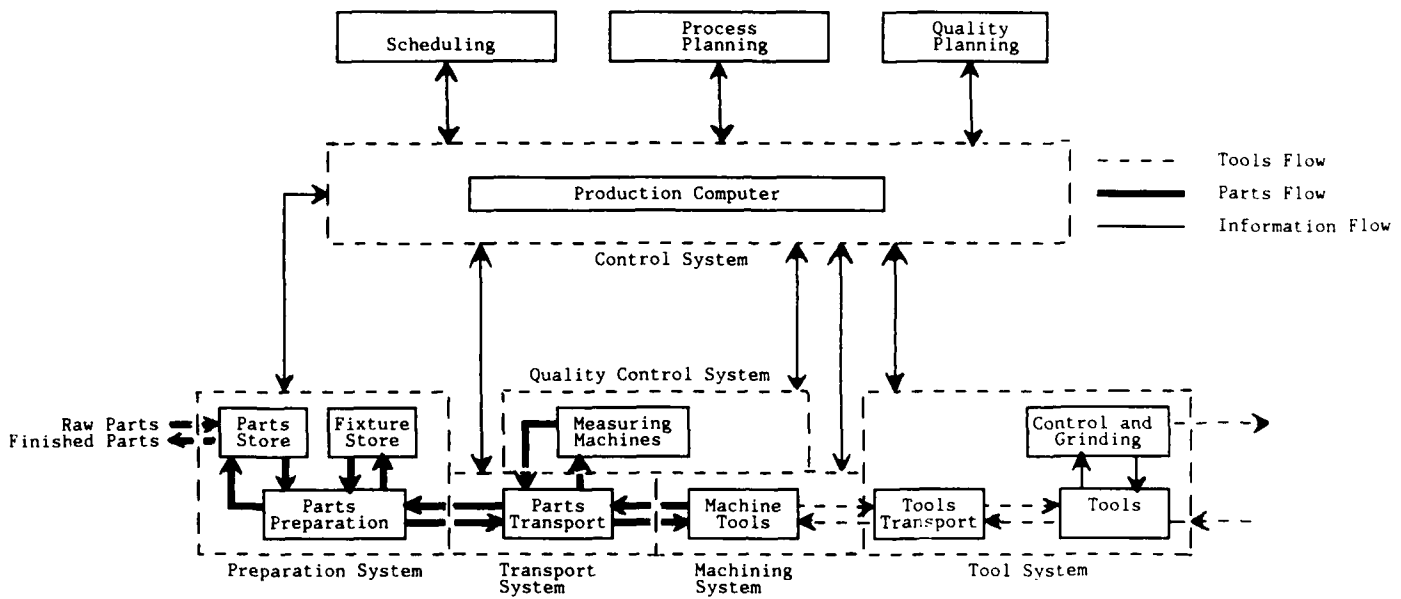


FIGURE 2-4 General form of a flexible manufacturing system (Bilalis and Mamalis, 1985).

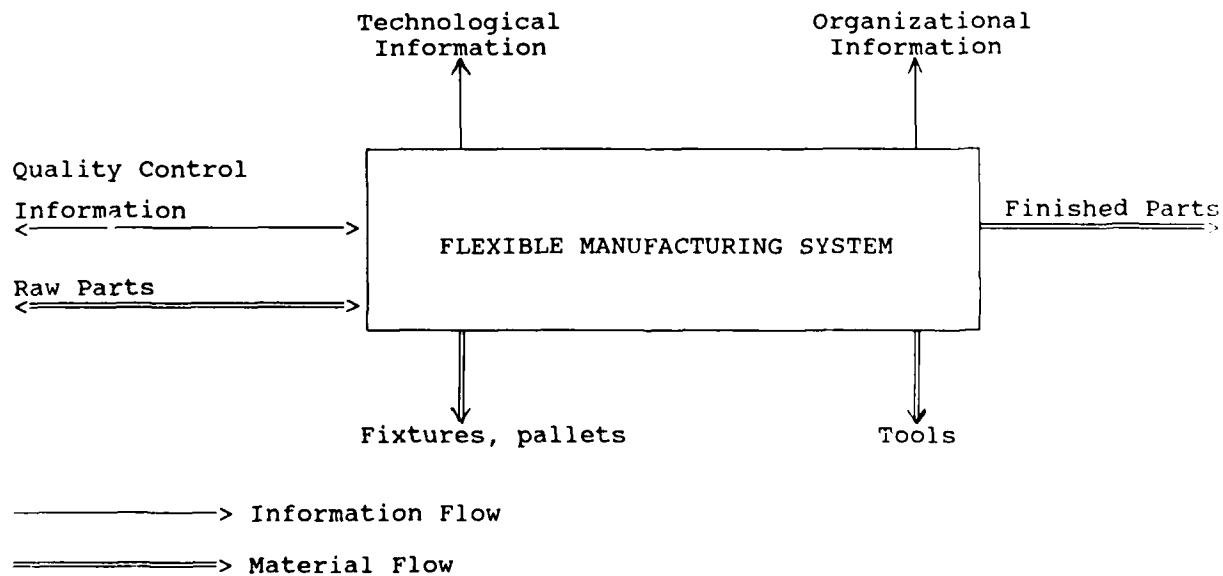


FIGURE 2-5 Functional elements of a flexible manufacturing system (Bilalis and Mamalis, 1985).

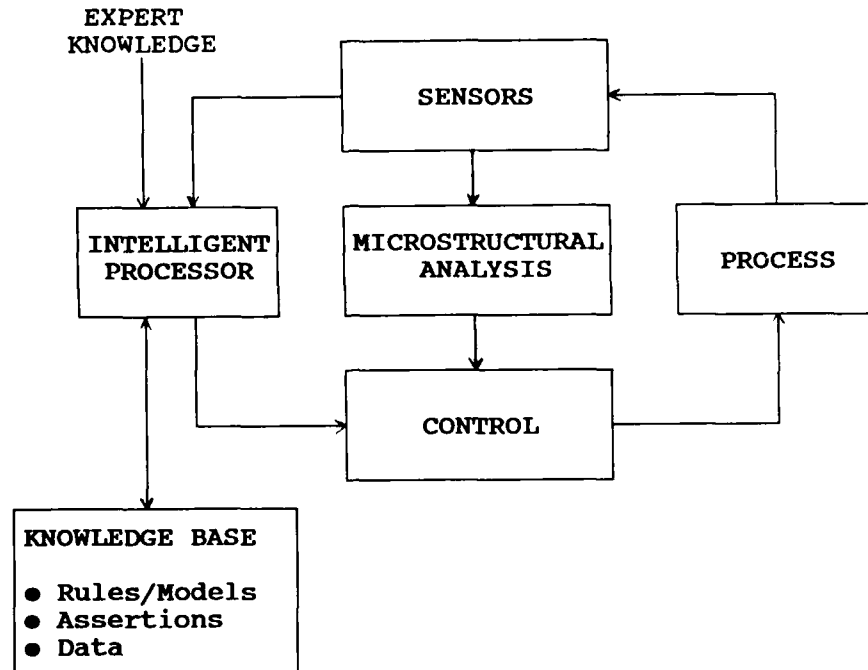


FIGURE 2-6 Intelligent processing of materials (Parrish et al., 1986).

TABLE 2-2 Factors in Intelligent Processing of Materials

AI Requirements	Materials Processing
Do experts exist?	Yes--the materials scientist, process engineer, and technicians
Are heuristics used to facilitate interpretation of sensor information?	Yes
Is the domain specific knowledge accessible and compatible with current knowledge-base limitations?	Depends on the materials system
Are the solution strategies well defined?	Yes
Is required decision information available?	Yes, from multiple inputs: sensors, visual observations, process models, material history
Are process kinetics decision time frames compatible with AI system computation times?	Depends on the materials system

time, bandwidth, and resolution relative to the applications associated with on-line control. The tremendous increase in readily available computing capability and advances in sensor methodology hold great promise for the future of sensors with specific data acquisition capability. These will be tailor-made for the applications involved in on-line control. The approaches used for sensing include x-rays, ultrasonics, eddy currents, acoustic emission, optical probes, magnetic probes, thermal detectors, and piezoelectric strain-measuring devices. The one common need for on-line control of metals processing is correlation between the sensor output and the material structural condition as well as response time consistent with the control process used. In Chapter 5 the details of the status of sensors for this application are reviewed and discussed.

#### REFERENCES

- Bilalis, N. G., and A. G. Mamalis. 1985. The flexible manufacturing system (FMS) in metal removing processing: An overview. J. Appl. Metalworking, Vol. 3, p. 400.
- Parrish, P., S. G. Wax, and B. Kushner. 1986. Intelligent Processing of Materials. Paper presented at the October 1986 ASM Meeting in Orlando, Florida.

## Chapter 3

### PROCESS UNDERSTANDING

A manufacturing process is based on a prescription of activities that transform a given set of raw materials into the final product. This prescription consists of a mixture of empirical and fundamental operations. In fact, the most critical frontier in the science of materials today is this boundary between the ability to make things and the fundamental understanding of the processes.

To compete successfully in the cost and quality of modern manufacturing, the practices of the past must be reconsidered, the total sequence of processes must be integrated and standardized, and on-line control must be practiced at critical steps. A decision regarding implementation of on-line control versus post-process testing can be made based on the complexity and real cost of the individual process step. Optimization for each materials system and the resultant property requirements must be based on understanding if the multivariant system is to be truly under control.

Process understanding makes possible three primary activities: (a) the definition of true process variables, (b) the choice of modeling approaches, and (c) the implementation of process models in on-line control. This total perspective suggests, as shown in Figure 3-1, that the installation of sensors does not necessarily yield process improvement. Sensors are but one component required of a design-for-manufacture approach.

### PROCESS VARIABLES

Every stage of materials modification involves one or more of the following processes: dimensional change, phase transformation, microstructure modification, and composition variation. The final state of the system is defined by the temperature, pressure, and chemical potentials present during processing, while the rate of application of the external stimuli determine whether this state is at equilibrium or metastable with respect to the environment. This four-dimensional space represents the freedoms of choice available in process design. The location chosen in this parameter space for a particular product is based initially on an understanding of the fundamentals of each elementary process and finally

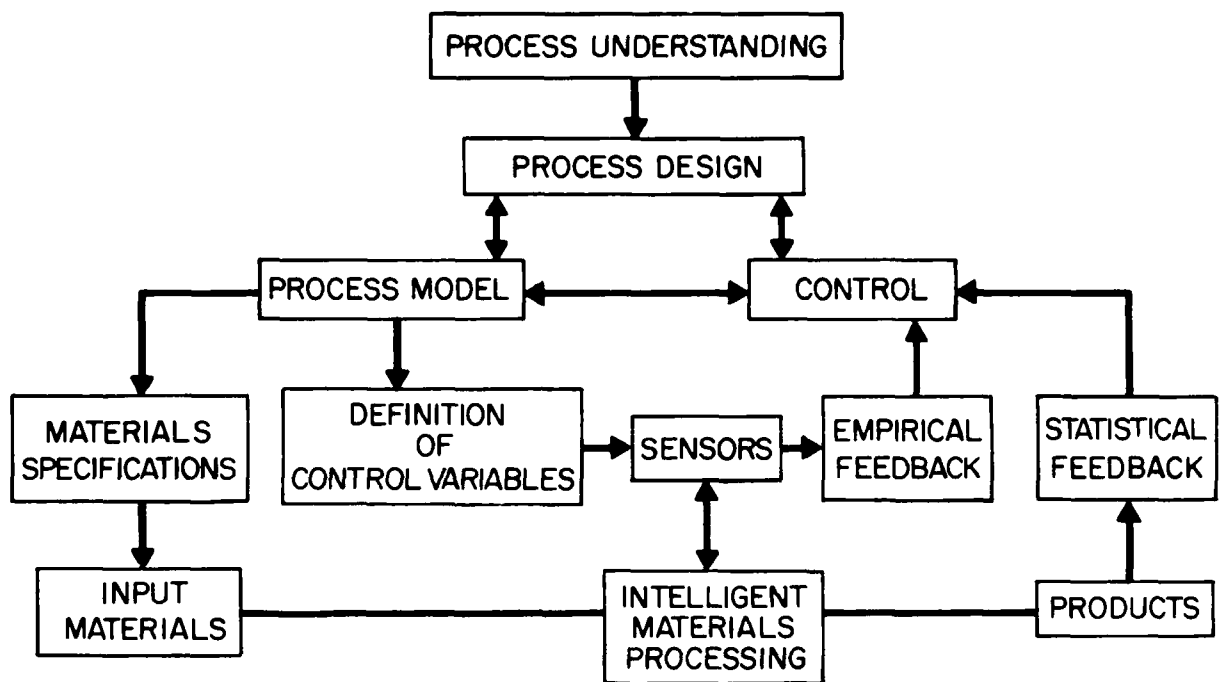


FIGURE 3-1 Activities involved in manufacturing.

on optimization based on the product and factory-specific requirements of heat and material flow and multiprocess compatibility.

A control variable is chosen from these process variables based on its criticality to the final material property requirements. In addition, the process should be designed to isolate the control variable and ensure its relevance to the end product. For example, to draw a single-crystal rod to a spool of single-crystal wire, a draw and anneal schedule is designed. The die increments and draw and anneal temperatures are control variables. Process understanding dictates that the orientation of the initial rod must be specified based on the operational slip systems and that the draw rate will display a given relationship to the draw temperature. This relationship will specify which process variable should be controlled. If that allowable draw rate depends exponentially on temperature, then the temperature must be controlled with precision, and a less precise feedback loop can control the draw rate. The time and temperature of intermediate anneals can also be specified by process deviations during prior draw runs.

Ideally, one practices end-point control by monitoring the primary, desired material property. Implementation of this procedure is straightforward when the desired property is dimensional. However, when a specific performance property is desired, fundamental materials understanding is necessary to choose the monitor mechanism and interpolate between process conditions and actual use conditions. For example, if mechanical reinforcement were the ultimate use of the single-crystal

wire, yield strength as determined by dislocation density should be controlled during the final draw and anneal. A high-temperature compatible monitor such as ultrasonic loss or internal friction could be employed, or a pattern recognition x-ray topographic system could be used.

In summary, fundamental understanding is the basis of the choice and implementation of process variables as follows: The process is initially designed for control. The critical process steps are chosen to monitor. The ultimate desired properties are chosen as end points. Process variables and, hence, control strategies are domain-dependent and fall into seven generic classifications: (a) temperature, (b) pressure, (c) composition, (d) size or spatial distribution, (e) gradient or depth distribution, (f) temporal distribution, and (g) physical properties. Sensors of the appropriate sensitivity, bandwidth, and ruggedness must be available and implemented according to the optimum process design.

### MODELING APPROACHES

Process modeling is the foundation of process design and implementation. The depth of the model determines whether process control will be on-line or off-line, as shown in Figure 3-2. Models are based on analytical or numerical data bases that describe the stimulus-response

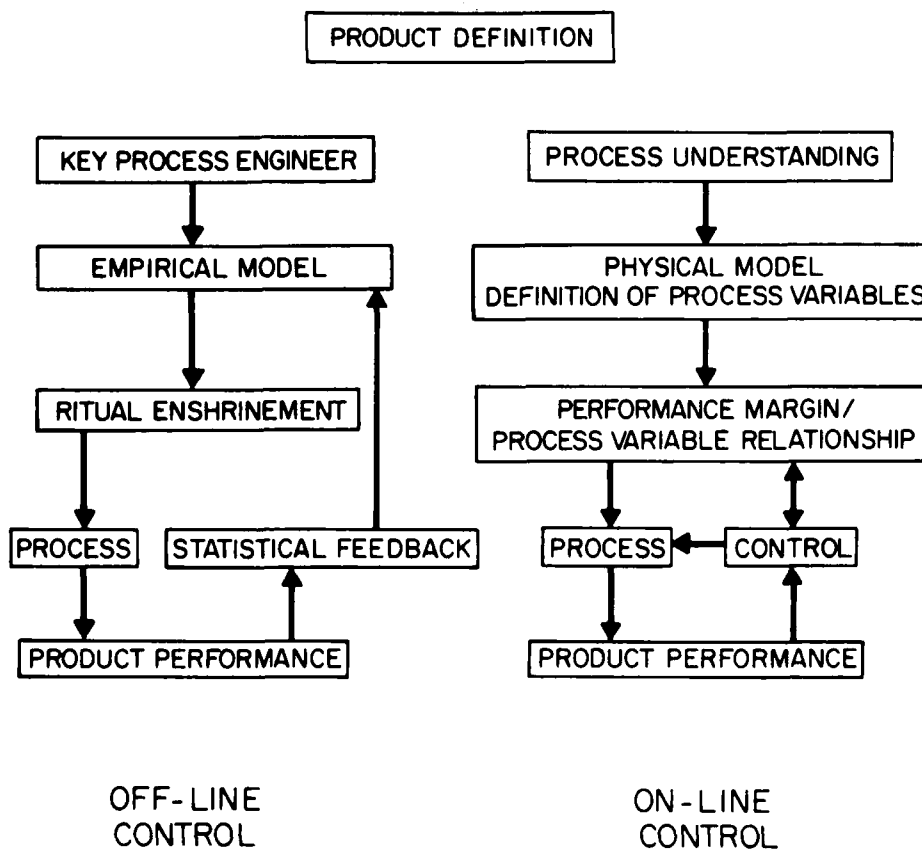


FIGURE 3-2 Choices in process design.

mechanism of a given materials system. These data bases lead to three classifications of modeling approaches: statistical, empirical, and physical.

*Statistical modeling* is based on analysis of end-product test vehicles. The structure of the process remains fixed, but process variables are modified to maximize product yield. Testing is performed at convenient intermediate stages as well. Results are correlated with the specific test stresses, and diagnostic conclusions are drawn from the statistical distribution of the mean-time-to-failure probability plot.

*Empirical modeling* is based on a data matrix from a particular process. All meaningful variables are controlled in a disciplined way, and the operating conditions are chosen from the table of results.

*Physical modeling* is based on fundamental process understanding. This approach provides essential guidance when processing demands are outside the range of the experimental data base. Design for control cannot be accomplished without the global perspective provided by physical modeling. Examples of the relevant data for this case are the basic principles of fluid flow, diffusion, and reactivity. Physical modeling is the primary source of insight for process improvement, addition of complexity, and new product design.

#### USES OF PROCESS MODELS

The ideal process model starts with specification of starting materials and ends with prediction of final properties. Two principles guide the role of sensors in materials processing: (a) The relationship of the control variable to performance margin must be well defined, and (b) the materials modification process should employ the methods and tools that are most amenable to control. Definition of process margin ultimately demands precontrol over variance by raw-materials suppliers, process control at the most critical steps, and simplification of the total manufacturing scheme. Understanding of true process margins is necessary to guide control in inspection, processing, and equipment maintenance and to establish fail-by-safe thresholds. Linking process selection to control provides for a self-regulating feedback mechanism. An integrated implementation scheme for process models is shown in Figure 3-1.

The ideal process, in this respect, utilizes tools that provide the signal to be monitored. Laser machining is a good example of the process providing the stimulus under control. The process point emits the light signal to be monitored, so that on-line temperature and dimensional control are naturally achieved. As a by-product, simultaneous three-dimensional shaping can be achieved at high tolerance in reduced processing time. More extensive use of lasers for rapid solidification, surface alloying, cladding, selective hardening, and zone annealing can take advantage of this enhanced relationship between process and sensor.

The primary objective with respect to on-line control is the prediction of process interactions and resultant properties in terms of

process variables. Expert systems can then be implemented to control production. However, it is equally critical to use process models to determine the "operating set point" of the production line. The sensitivity of process margins to changes in control variables must be central to process design. Process models should be used to sort production design alternatives until the least critical process is found. A good application of this concept is the use of differential thermal analysis to qualify master alloys for casting.

#### VLSI: A MODEL FOR MATERIALS PROCESS CONTROL

Implementation of on-line control in metal processing is limited by both tradition and technological obstacles. Product and process design for manufacture employing the most advanced models and sensors for control is the paramount technological challenge. However, plant investment is ultimately guided by economic analyses. The investment must be driven by a competitive advantage based on future yield and quality improvements. The primary basis of implementation is the concept of on-line control as a tool that can be used to continually lower costs. The advance toward very-large-scale integrated (VLSI) circuits in the electronics industry provides a materials processing paradigm for this report (Figure 3-3).

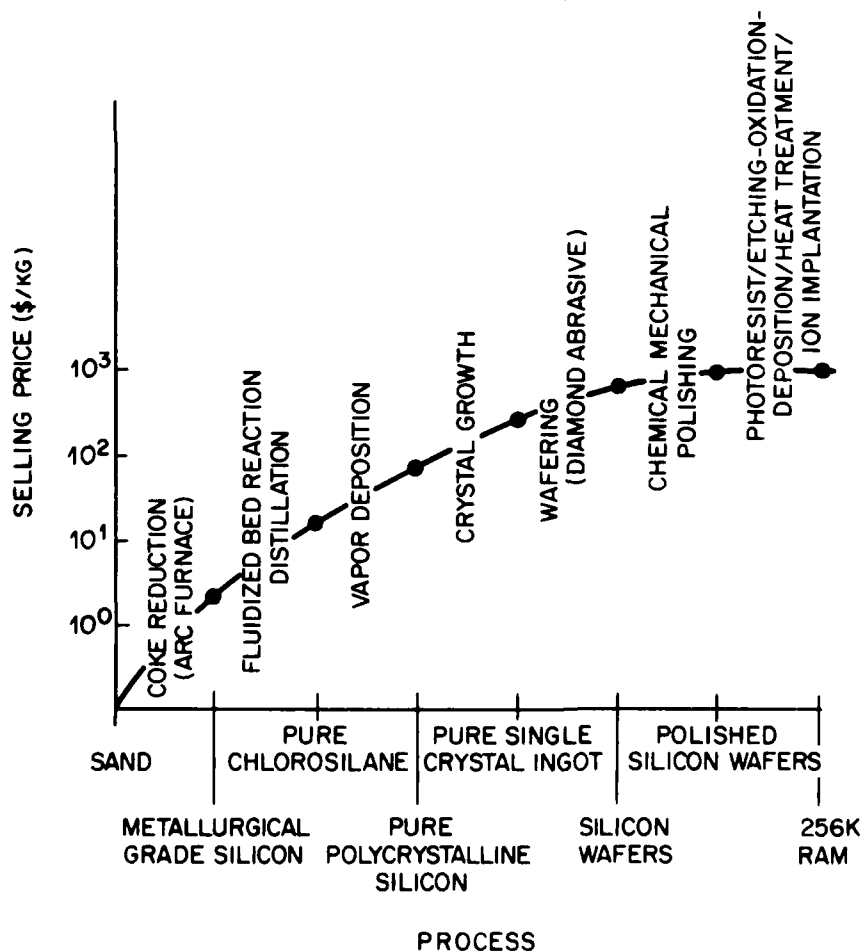


FIGURE 3-3 Silicon processing for VLSI: value added.



The industry averages a 25 percent turnover in plant equipment each year, with a major process upgrade every 2 years.

The challenge of VLSI is to be able to fabricate 106 transistors on a 1-cm<sup>2</sup> chip of silicon and to reproducibly manufacture millions of such chips. The primary materials processing problems are (a) the production of pure, perfect single-crystal silicon, (b) maintenance of cleanliness throughout the processing sequence, (c) the definition and fabrication of micrometer-scale features, (d) reproducible positional accuracy of 0.01  $\mu\text{m}$ , (e) control of materials composition and properties at the atomic level, and (f) production of films of 100-Å thickness with precise reproducibility. A 10,000 ft<sup>2</sup> plant is projected to reach mature production within 2 years of start-up and generate approximately \$250,000,000 per year in revenue. A typical plant operates in a flexible manufacturing mode with a fixed set of processes (such as photoresist, etching, oxidation, deposition, heat treatment, ion implantation) to produce a variety of integrated circuits. The processing variables and integrated processing sequence are determined by extensive modeling, which literally accounts for each atomic jump during manufacturing. Production is run for three shifts on 7 days a week with in-line maintenance in order to meet the high plant depreciation rate.

Under current optimized conditions, silicon materials processing remains operator-intensive and batch-oriented, with little automation. Each plant upgrade now incorporates added physical automation and automatic control, with capabilities for large-area, single-wafer processing. The key control implementation problems are (a) overall process complexity, (b) a rapidly changing technology, (c) the limited payback for isolated implementation, and (d) loss of the economies of scale. The main driving forces for change are (a) the need to handle larger wafers, (b) the inadequacy of subjective judgment, (c) the irreproducibility of operator control, and (d) the requirement for a "leading edge" plant to meet market demands. The economic justification is yield and quality improvement. The initial operation may not meet depreciation, but operating costs are independent of yield. Each 1 percent increase in yield can add \$5,000,000 to 10,000,000 in revenue. The benefits of automatic handling and process control are therefore obvious. Given state-of-the-art equipment, technology, and process models, the challenge of the future is computer integration for process control: definition of an equipment interface protocol, automatic wafer identification for data entry and control, work stations to extend equipment functionality, generic work-cell controllers, network controllers, and expert systems for enhanced control and decision-making.

## PITFALLS

The full implementation of process modeling in the design and control of metal processing is at least a decade away. Current approaches to process design and implementation can be misleading. This condition arises from two primary limitations: the absence of a practical "mindset" that can properly estimate the cost of test vehicles, define reasonable yield, and evaluate "discipline-induced quality" against "hit-or-miss problem-solving" and a lack of fundamental knowledge and commercially

available equipment. If this situation is not remedied completely, on-line control may degenerate into merely a proliferation of sensor installations with complexity and fault intolerance as the result rather than simplicity and quality.

Sensors are still viewed as a weak link in "intelligent" solidification processing. A complicating issue with sensor development is the lack of basic knowledge of the relationship between sensing mechanisms and microstructure. Furthermore, the hostile environment in which sensors are needed (high temperatures and aggressive atmospheres), the limited time available for on-line process control, limited accessibility, and the need to avoid interference with the process itself all introduce constraints on practical sensor systems.

Many investment casting processes involve solidification rates that allow sufficient time for on-line process control to influence microstructural integrity. The key in situ sensor measurements required for control are monitoring of the liquid-solid (LS) interface position and shape and determination of the thermal gradient (G) at the LS interface. The solidification rate (R) can be easily derived from the LS position and withdrawal rate. The propensity for many of the defects found in castings (equiaxed grains in oriented or single-crystal blades, freckles, low-angle grain boundaries, etc.) can be expressed by considering both R and G, as shown in Figure 3-4. Control schemes can be designed to monitor LS and G and regulate controllable casting parameters, such as withdrawal rate, and enhance the casting integrity. There are a number of sensor techniques, such as ultrasonic, eddy current, x-ray, laser, infrared, and acoustic emission, that should be examined for on-line monitoring of the LS and G. Unfortunately, no framework exists for evaluation of appropriate sensor schemes, and the possibilities remain numerous.

As on-line sensors, in combination with process models, are implemented, the need for post-process evaluation will decrease. Not only can the on-line information be implemented in "intelligent" material processing, but also the information can be used to identify locations of potential deviate casting integrity. This "margin point" could be detected directly by the sensor or predicted by the process models using sensor data as boundary information. This mechanism defines selective post-inspection locations for deviate casting integrity and eliminates costly 100 percent inspection.

#### PROCESS MODEL RESEARCH

Research in process models consists of two primary fields of endeavor: (a) continuum approaches to heat and fluid flow and (b) atomistic approaches utilizing Monte Carlo statistics or molecular dynamics. Both fields are based on numerical simulations that are computationally intensive. In fact, this research is the largest application driving force behind the development of large parallel processing computers. In general, as a model becomes more physically realistic (i.e., close to first principles), it contains fewer adjustable parameters and greater predictive capacity.

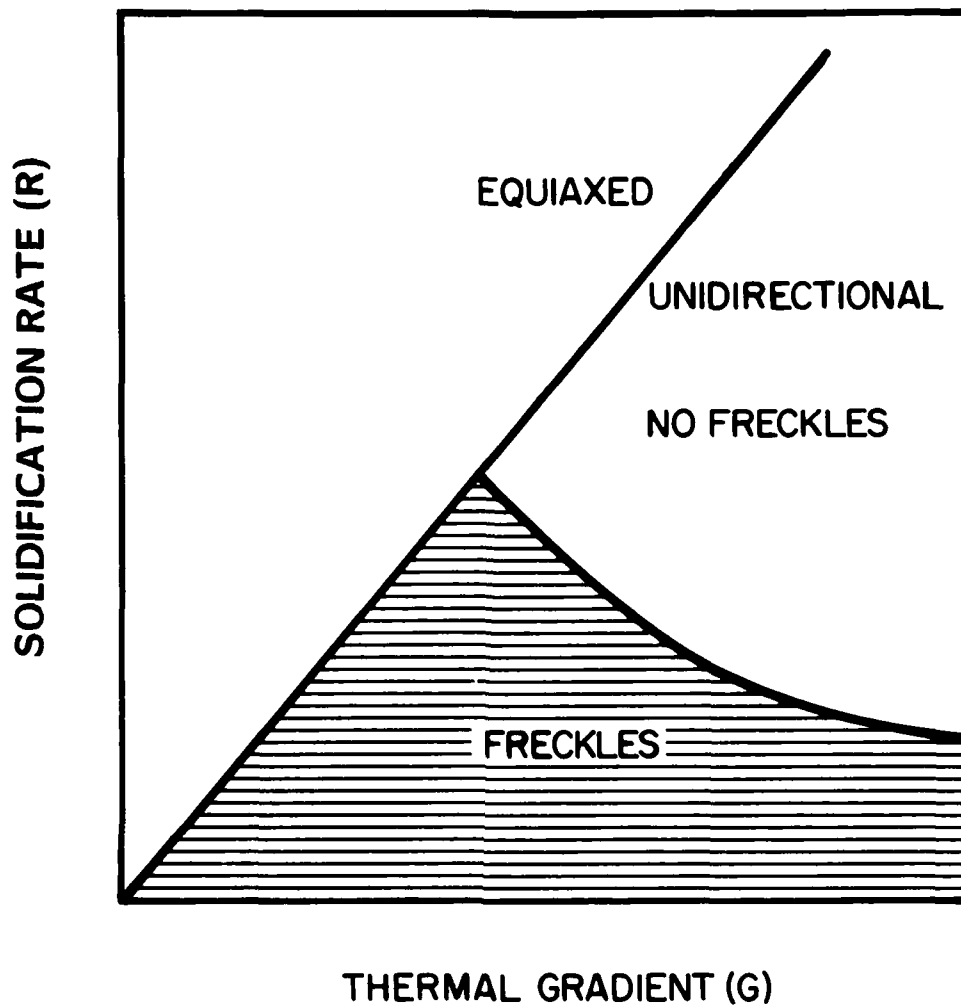


FIGURE 3-4 Defect criteria map.

Two subjects that are critical to intelligent materials processing are missing from current research priorities: simulation of microstructure in the  $10$  to  $10^4$ -Å dimensional range, and the incorporation of local chemical kinetics into continuum models. The topographical problem is exacerbated by the lack of computer power in this mesoscopic regime and the absence of a terminology that can quantify heterogeneity of microstructure. Some generic areas of required phenomenological understanding that limit the introduction of process control are given in the following examples.

- *Chemical vapor deposition* is the preferred batch process for surface modification of materials (from economic considerations). However, no scheme of on-line control is in practice. The fluid dynamics and chemical kinetics of the process have yet to be included in an integrated process model.

- *Crucible-free casting* with magnetic field containment possesses inherent advantages in surface finish, perfection, and process control. However, process design has been limited by the need to include heat of fusion and liquid-solid interface motion into the continuum model.
- *Optimization of blast furnace and smelting operations* requires better modeling involving chemical kinetics and thermodynamics.
- *Welding* is a frontier where only empirical modeling has thus far been able to include the complex chemistry, heat and mass flow, phase transformations, and role of protective environments.
- *Rapid solidification processing* has benefited greatly from heat flow and phase transformation modeling.
- Critical applications of *powder metallurgy and dispersion strengthening* in advanced materials await process simulations at the computationally inaccessible length scales of 10 to  $10^4$ -Å. Although models and experiments on resultant properties are in good order, no formal modeling of processing has been developed.
- *Extraction processes* can involve shock wave fracture, milling, and fluidized bed processing, which have never been truly optimized by process modeling.
- *Sheet forming* was significantly improved by simple considerations of crystal plasticity and deformation processing. Stamping and continuous casting address key concerns of two-dimensional deformation based on the initial grain size and texture.
- *Superplastic deformation* relies on a very fine grain microstructure and an intimate knowledge of the grain boundary slip and strain rate interrelationship.
- *Extrusion modeling* describes the interplay between polycrystalline texture and single-crystal slip systems.
- *Single-crystal turbine blades* are the most visible successes in advanced materials processing. However, these processes have resulted primarily from empirical modeling with minimal cost constraint. They may not yet be optimized from either a cost or performance criterion. On-line control is not practiced now.

Research in process modeling will establish two building blocks for the intelligent processing factory: definition of process variables, performance margins, and feedback interactions that will ensure fine-scale reproducibility and a push of computer hardware and software development to a stage where factory integration is a real possibility.

## SUMMARY

One of the greatest limitations to on-line control of metal processing is basic knowledge: process understanding to define true process variables and margins, and the physics of materials that links

sensor output to materials properties. Process model research provides both this fundamental understanding and an applications driving force for the development of needed computational hardware and software. Process control requires a feedback loop that integrates sensor output with process understanding. Process selection and design should be predicated on the optimal functioning of this loop. The most fundamental models possess the fewest adjustable parameters and hence the greatest predictive capacity. The economic advantages of sensor and model control are found in reproducibly increased yield and quality. Operating costs are independent of yield, so process refinement produces permanent revenue increases.

#### BIBLIOGRAPHY

- Szekely, J., J. W. Evans, and J. K. Brimacombe. 1988. The Mathematical and Physical Modeling of Primary Metals Processing Operations. New York: John Wiley & Sons.
- Chandra, J., and R. P. Srivastav (eds.). 1987. Constitutive Models of Deformation. Philadelphia: Society for Industrial and Applied Mathematics.
- Johnson, W., and P. B. Mellor. 1973. Engineering Plasticity. London: Van Nostrand Reinhold Company.
- Backofen, W. A. 1972. Deformation Processing. Reading, Massachusetts: Addison-Wesley Publishing Company.

## Chapter 4

### CONTROLS

The preceding chapter discusses a generic manufacturing process as a series of activities that is used to transform raw materials into finished products. Usually the overall commercial process consists of many activities or elementary operations that are executed in a systematic fashion to provide for a consistent and predetermined material flow. The global and local regulation of these elementary operations is process control.

#### RAW MATERIALS AND PRODUCTS

The overall objective of a manufacturing process is to convert raw materials to a final product, as the material is passed from one elementary operation to the next. A successful process must consistently satisfy the requirements of the goal state while accommodating all the intrinsic properties and variations of the feedstock in the initial state. Once the initial and goal states are fully characterized, the process must comply with an imposed set of manufacturing considerations. Since the paramount objective of most commercial processes is adding value, these considerations are usually economic. Other factors such as safety and temporal issues may also be significant and may strongly affect the architecture of the process.

Most commercial metals processes comprise a repetitive execution of the elementary operations that are intended to consistently achieve the goal state. Control is axiomatic with repetition and consistency, and therefore prudent process control is germane to the efficacy of the manufacturing activity. This chapter considers the elements of control in metals processing on both discrete and holistic levels.

#### IMPROVEMENT NEEDED IN METALS PROCESSING CONTROL

In a previous National Materials Advisory Board (1986) study, a need for enhanced control of ceramic and metal powder production was identified. The study perceived inadequacies in real-time data collection, data manipulation, and operating devices for subsequent process control. It could be inferred from the report that the production of certain types of powders may not even be possible without on-line process control.

Process control becomes an essential, enabling technology in and of itself.

Similar recommendations calling for the improved control of powder production also apply in other metals processing scenarios where

- The product involves exceptional properties that can only be achieved by operating the process within a narrow band of stability.
- Economics and/or production versatility requirements dictate using flexible manufacturing system methods.
- Close human operator intervention is not feasible.

The previous chapter discussed the production of perfect single-crystal silicon wafers for VLSI applications, which is indeed a good example of an exceptional scenario. Other commercial examples of exceptionally stringent process control requirements include the control of internal defect size in damage-intolerant superalloy turbine discs (Koff, 1984) and inclusion, microconstituent, and composition control in superplastic aluminum alloys (A. K. Vasudevan, internal corporate correspondence, Alcoa Company of America, 1985).

Flexible manufacturing systems (FMSs) are a subset of computer integrated manufacturing concepts and are highly control-intensive on both the elementary operation and global process scale. Numerous successful applications of FMSs have been cited in polymer processing (Yang and Lee, 1986a,b), composite production (Postier, 1985), metal forming (Mamalis and Bilalis, 1986), and metal machining (Jablonowski, 1986). Obviously, FMS concepts are more amenable to those industrial sectors involving traditionally well-controlled operations such as metals machining. The implementation of FMSs in the primary metals industry, however, cannot readily be accomplished with current difficult-to-control processes. The primary metals industry, for example, has been developing entirely new technologies capable of adaptive control for a planned flexible ingot manufacturing facility. These technologies must come to fruition before such a facility is possible.

Factory-in-space materials processing and the preparation of hazardous substances (i.e., processing of plutonium) constitute another extreme scenario.

The general methods of process control enumerated in Chapter 2 were feedback control, feed-forward control, intelligent control, hierarchical control, and artificial intelligence. A process control loop is the fundamental component in each of these methods. The number of control loops, directionality of information flow, sophistication of the controller, and coupling of multiple loops determine which general control method is used.

## DISCRETE LOOP PROCESS CONTROL

The controller (Figure 1-1) determines the robustness of the control loop. In its most basic form, the controller is a device that compares

the control variable with a setpoint and simply switches the manipulated variable on and off when a difference (error signal) exists. A dead band is typically employed in the controller to limit the response of the comparator until the value of the difference reaches a threshold value. Originally, electromechanical relays were used for switching, but silicon-controlled rectifiers are employed in modern controllers. The household thermostat is an example of an on-off controller.

Improved process control is usually obtained when the comparator forces a manipulated variable proportional to the magnitude of the error signal through a predetermined gain constant. The controller hardware requires either a vacuum-tube or solid-state amplifier for proportional control.

Further controller sophistication imparts an additional modification of the manipulated variable through time integrating and derivative functions. The purpose of these functions is to dampen instabilities and oscillations that compromise the precision of control. The so-called proportional-integrating-derivative is a three-parameter controller requiring more elaborate electronic hardware. Values for the proportional gain and integrating and derivative constants are adjustable to provide optimum process control tuning.

Modern integrated circuitry has reduced three-parameter control hardware to simple plug-in modules. In more complex processes involving several discrete control loops, a programmable controller is used with preprogrammed values for the control parameters. A complete description of programmable controller hardware can be found in texts such as Gilbert and Llewellyn (1985). Details of process control methods are discussed in Coughanowr and Koppel (1965).

In feedback control, a process parameter sensor feeds information back to a controller that subsequently invokes a change in the manipulated variable. Many industrial processes are often a consolidation of several discrete control loops. Each loop controls specific operating parameters within the global process. Parametric compliance to a fixed setpoint value is achieved, and no modification of the setpoint occurs based on changes that may take place at some other point in the process. In the event that some unanticipated perturbation disrupts the process, human operator intervention is usually required to adjust one or a series of other parameters for correction.

The continuous casting of an ingot illustrates the integration of several discrete process control loops to provide multiloop control of a manufacturing operation. Continuous casting has been used for many years to economically solidify metals such as aluminum, steel, copper, magnesium, and others while providing a controlled macrostructure and solidification substructure. In this process, molten metal continuously flows from a holding furnace into an open-bottom mold. The process begins by raising a chill block into the bottom of the mold, allowing a solidified shell to form, and then lowering the chill block at a speed commensurate with the metal flow rate. Solid ingot is progressively withdrawn from the bottom of the mold. The necessary heat rejection is accomplished by circulating coolant through the mold and by direct



impingement on the ingot surface as it exits the bottom of the mold. Process control occurs when the heat and mass flows are equilibrated at a rate required to provide the correct ingot structure. Alloys with a wide coherency temperature range necessitate particularly careful process control.

Continuous ingot casting facilities use control loops for regulating several specific elements in the process. Each controller will not have control authority outside the domain of the loop, even though the loops may be physically coupled.

A schematic representation of the simplified casting process and the discrete loops is shown in Figure 4-1. In this example the three loops control metal temperature, casting rate, and mold coolant flow rate. The mold coolant flow rate loop consists of a volume flow rate sensor, proportional controller, and servo-operated flow control valve. The heat influx to the mold is contributed by the product of the sensible heat of the incoming molten metal and the mass flow rate (casting rate). Under steady-state conditions, this is equilibrated by coolant flow to the mold and outgoing sensible heat in the solidified ingot. The latter, along with casting rate, metal temperature, and other parameters, is preset and dictated by the standard casting practices for a particular alloy and ingot size.

The human operator of this casting unit has supervisory control over the process. He is relied on to be cognizant of incipient changes in the

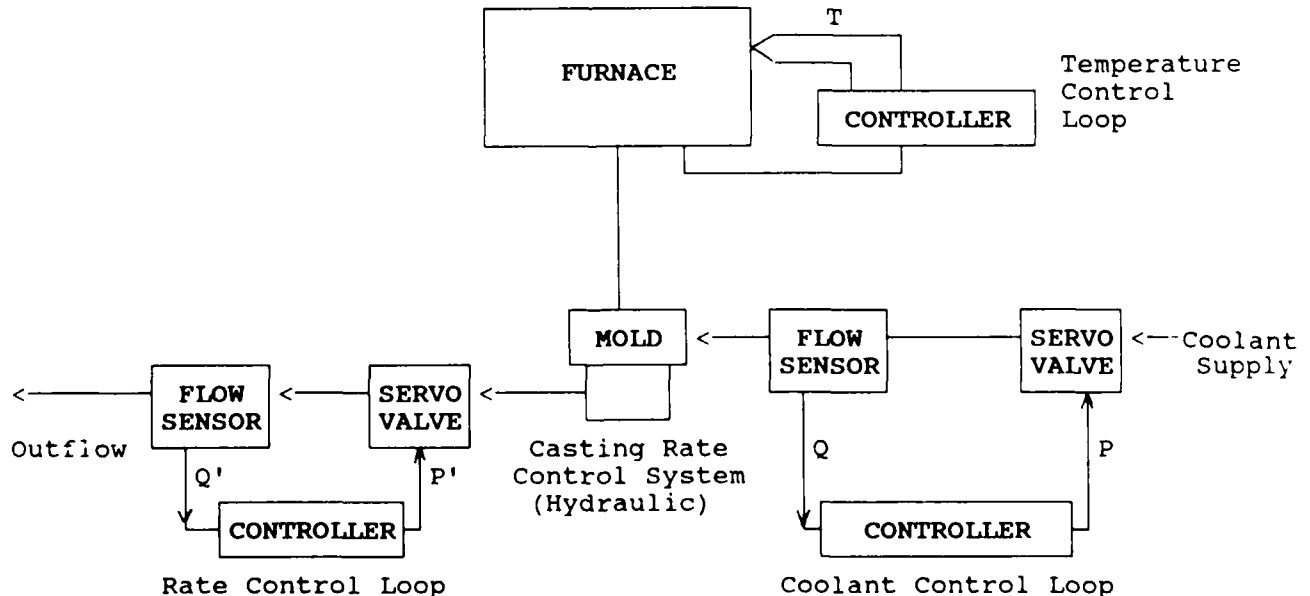


FIGURE 4-1 A continuous ingot casting process with three discrete control loops.

process and to respond by setpoint modification to maintain stability. The operator's input data set generally consists of visual clues and monitoring of instruments. If the operator noted a significant change in incoming metal temperature, for example, he would respond by manually modifying the setpoint of the casting rate loop in an effort to maintain thermal equilibrium.

Consider, however, a case where the thermal equilibrium of the process is disrupted by a decrease in the boiling heat transfer characteristics of the coolant. Since this parameter is not monitored in real time, the only on-line information available would be a change in ingot surface that the vigilant operator could observe. Noting this change, the operator would reduce the casting rate by an amount based on his past experience. A degree of thermal equilibrium would be restored, as evidenced again by the operator's visual clues. A catastrophic termination of the process would probably not occur.

Ingot surface appearance changes detected by the operator are a second-order effect caused by a reduction in the thermal gradient/growth rate (G/R) ratio. These fundamental solidification parameters are not directly monitored or controlled in this example. The G/R ratio control limits that the operator responds to are represented by ingot surface and extend well outside limits to ensure total ingot quality. Since as-cast ingot grain size and morphology are critically sensitive to G/R ratio, a macrostructurally unacceptable ingot was probably cast. The operator's response was palliative, and off-line inspection of the ingot would reveal a coarse grain size.

This simple example illustrates the limitations of an ingot casting process controlled by multiple discrete loops. First, a potentially unreliable operator must observe second-order changes in ingot surface to detect the problem. He is unaware that the solidification isotherm in the ingot has migrated or that the as-cast grain size is too coarse. Second, the operator formulates a heuristic response based on his observation of change. For example, if the ingot surface looks hot, reduce the casting rate by 25 percent. The more appropriate response of reducing casting rate and increasing mold coolant flow rate would probably not be implemented. Third, the operator's response is not self-tuning or iterative. If a 25 percent reduction in casting rate improves the ingot surface, the operator stops. Finally, the primary real-time information used by the operator was a subjective visual clue that he obtained himself. Ingot quality as related to macrostructure was ascertained post mortem by off-line inspection.

Two basic approaches may be used to resolve the solidification problem previously described. The first method requires the development of constitutive equations that quantitatively describe relationships between solidification parameters and changes in macrostructure. For example, the ingot macrostructure,  $M_i$ , may be a function of these solidification parameters:

$$M_i = f_i(S_1, S_2, S_3)$$

where the set consists of local solidification time, temperature, and heterogeneous nuclei concentration. Since it is not practical to measure this latter parameter directly, it may be further a function of

$$S_2 = F(\text{Ti}, \text{B}, \text{Zr})$$

where Ti, B, and Zr are titanium, boron, and zirconium concentrations, respectively. Titanium and boron form intermetallic compounds that are useful for grain-refining aluminum alloys, while zirconium has a negative interaction.

Since a rate equation is required for control purposes,  $\dot{M}_i$  could be expressed as

$$\dot{M}_i = g(S_1, S_2, \text{Ti}, \text{B}, \text{Zr})$$

Acceptable control of ingot macrostructure will be accomplished provided that the equation is validated by experiment and the solidification process is homogeneous. Sensors providing solidification interface position (related to solidification rate), local metal temperature, and chemical information can be incorporated into the process as input variables, and the dependent variables of casting rate and mold coolant flow rate are deduced from control algorithms based on the constitutive equations. A macrostructurally acceptable ingot is ensured, and relatively simple sensors are used.

The second method of controlling the casting process is based on direct monitoring the principal process variable(s) and generating manipulated variables from relatively straightforward control methods. In the case of an ingot casting example, a sensor to continuously measure grain size and assess grain morphology is required. With this input, the process variables of casting rate and coolant flow rate can be directly controlled from algorithms. The control parameters (i.e., gain) may either be determined semi-empirically by open-loop testing or predicted from simulation modeling, or both.

The success of this second approach is predicated entirely on the identification and measurement of the principle process variable. While the actual process control tasks are relatively straightforward, a complex sensor is required. In cases where such a sensor is available, the direct control method is more stable, versatile, and generally more desirable. If the sensor is subject to random noise detection or if macrostructural inhomogeneities are detected, digital filters and stochastic control methods may be used to improve control stability.

#### FEED-FORWARD CONTROL

Feedback control always collects information from a process parameter sensor and uses the manipulated variable to retroactively control the process. Information is not passed forward to the next operation for regulation purposes. Complex material flow processes such as FMSs or processes with high inertia cannot be adequately controlled using antecedent information in a feedback capacity.

In feed-forward process control, the directionality of information flow is changed to modify subsequent operations in the process. Deviations from the goal state are accommodated by adjusting the characteristics of these operations in a compensatory manner. This is particularly important when the response time of a system is poor. An example of poor response time would be a melting furnace with high-thermal-mass refractory walls. Simply charging material to the furnace followed by the application of heat would result in an extended meltdown time. If information regarding the impending addition of charge material was fed forward to the furnace controller, the furnace could be preheated in advance. Meltdown time would be substantially reduced, and material flow through the overall process would be enhanced. Proportional feed-forward control would further modify the process by preheating the furnace by an amount proportional to the sensible heat of the incoming charge.

Feed-forward control has the capacity to mitigate upstream processing errors and increasing overall product quality. If the ingot casting unit in a previous example had information that incoming metal temperature was increasing, an appropriate change in coolant flow could be effected to minimize the effect of the temperature change. The sophisticated feed-forward controller would monitor the metal temperature trend and gradually adjust the coolant flow in a complementary manner to ensure the quality of the ingot.

Feed-forward control can be an integral part of intelligent control, which is described next.

## INTELLIGENT CONTROL

The first solution to the previous ingot casting control problem monitored secondary process variables and used a predictive model to derive the manipulated variable. In the second solution, a complex sensor measured the principle variable (grain size) directly and did not require a sophisticated predictive model for control. Certain metal processing control applications exhibit system dynamics or sensor limitations that necessitate both monitoring of the principle process variable and the use of models. This need emerges in the case where long transport delays or low sensor sampling frequency excessively dampens response. A more complex controller that relies on additional input variables and incorporates a model of the process can be used successfully in cases where physical limitations restrict sampling frequency and/or impose transport delays. Such "intelligent" controllers use a set of differential equations representing the dynamic response of the system and secondary input variables in an anticipation scheme that will result in stable control. In some cases the controller may also vary control parameters such as gain as the controller steps through several time domains or enters a different control regime. This so-called adaptive control technique is useful to maintain control stability during transients such as are imposed during a start-up condition. Although intelligent controllers are typically hosted on a computer, the control algorithms respond in a completely predetermined manner and therefore do not qualify as artificial intelligence.

A schematic diagram of an intelligent controller is shown in Figure 4-2; it should be contrasted with the simple controller of Figure 1-1. In this case the setpoint value  $R(t)$  is compared to the input value  $I'(t)$  by comparator 1. The resulting error signal  $\epsilon$  generates the manipulated variable,  $M'(t)$ , from the algorithm in the controller. Rather than  $M'(t)$  manipulating the process operator directly, its value is modified by an anticipated feedback  $Y(t)$  from a differential equation representing the process. The inner control loop in essence regulates the process in a manner that equilibrates the anticipated and actual input. Although  $I(t)$  is the actual input value, it is modified by a simulation of the process and does not directly generate  $M(t)$  through a set of fixed algorithms.

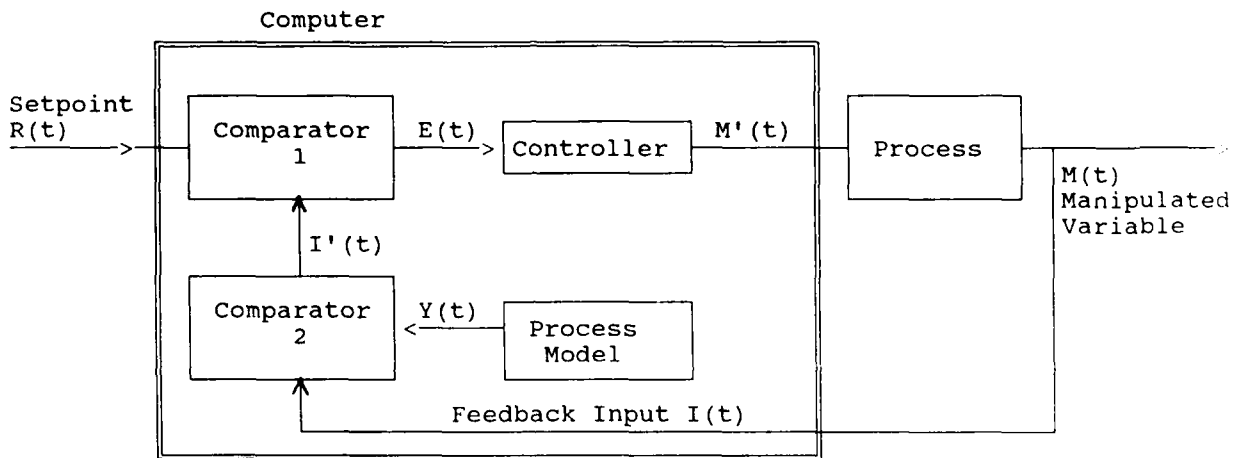


FIGURE 4-2 Controller incorporating process model.

A good industrial example of an intelligent controller application is on-line molten metal composition (chemistry) control. Real-time molten metal composition control is of at least topical interest to organizations interested in flexible solidification processes and is considered to be an enabling technology for such FMSs. The initial state is an unalloyed metal stream that continuously issues from a melting unit, while the goal state is a specification alloy that will be continuously supplied to a solidification device. The control objective in this particular example is to regulate the mass flow rate of alloying materials to control alloy chemistry within a 2 percent error band, although external system perturbations may create a metal flow rate variation greater than 20 percent in 10 seconds. The process is shown in Figure 4-3.

Unalloyed molten metal enters the alloying device from the melting unit. Alloying elements are added at the appropriate rate in the alloying device and homogenized in a large stir tank mixer. The analytical sensor

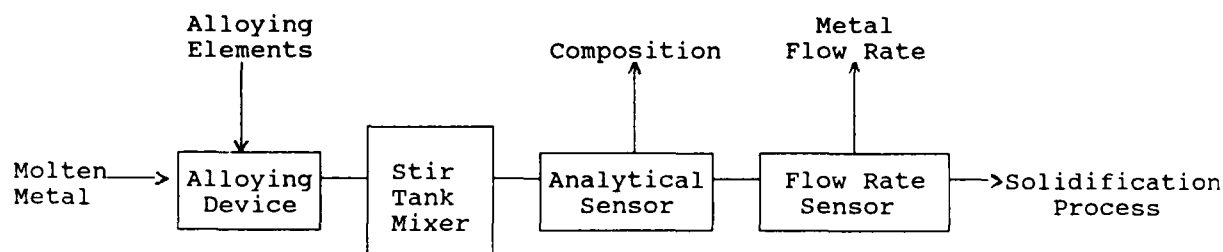


FIGURE 4-3 Real-time molten metal chemistry control.

monitors alloy composition at a frequency of one sample per minute, and the metal flow rate sensor provides an essentially continuous output.

Metal flow rate through this system is of the order of 100,000 lb per hour, and the obvious control problem is the dynamic lag imparted by the high-time-constant mixer coupled with a long sampling interval. In this case, the required control limits cannot be satisfied by relying exclusively on principal control variable (chemistry) information delivered by the analytical sensor. Secondary control input is provided by a mass flow rate monitor that is capable of continuous output. The intelligent controller must integrate these inputs with a mathematical model representing the mixing characteristics of the mixer and all other transport delays.

#### FLEXIBLE MANUFACTURING SYSTEMS AND HIERARCHICAL CONTROL

The concept of flexible manufacturing systems was alluded to earlier in this chapter. Many industrial organizations are expending a considerable effort to develop and implement FMSs as expeditiously as possible. The FMS is presented here not as an intrinsic process control technique but as a special example of a control strategy.

The FMS is a just-in-time, automation-intensive production system with the capability of producing an expanded range of products with minimal manual intervention. Overall system management is accomplished by a computer, and the system is thought of as paperless. A particularly desirable characteristic of FMSs is a make-to-order capability, thus obviating an extensive inventory. Statistical process control concepts are inherent with FMS operation, as intermediate and final product quality is fed backward and forward to diagnose and correct system anomalies.

A flexible ingot manufacturing system (FIMS) is a FMS structured to provide made-to-order, just-in-time, high-quality ingot. An important part of the FIMS is a flexible in-line metal treatment system. This system most literally accepts molten metal from a melting unit that is potentially unalloyed and may be contaminated with dissolved and suspended impurities. The in-line system must perform all the necessary functions to convert this metal stream into usable feedstock for the subsequent solidification process. The elementary operations include chemical purification, filtration, alloying, and real-time analysis to produce this

feedstock. Before describing the flexible in-line metal treatment system, it will be useful to consider conventional technology. Figure 4-4 shows a conventional aluminum metal treatment system.

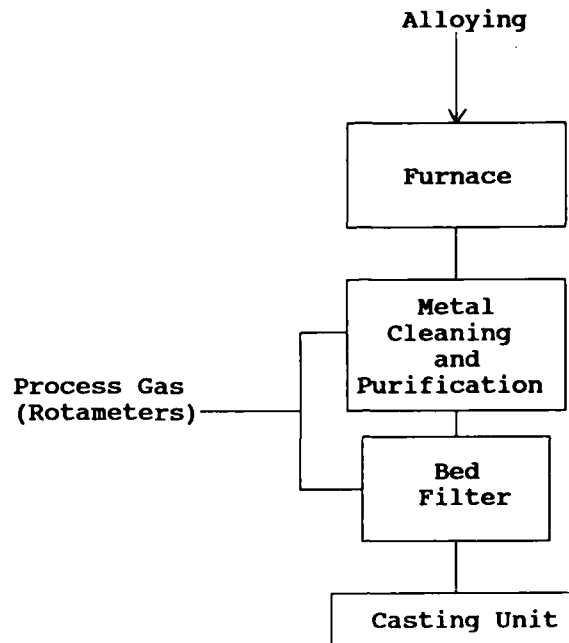


FIGURE 4-4 Conventional metal treatment system.

Alloyed aluminum issues from a furnace into an in-line fluxing device where the metal is purified. Process gas is metered to the fluxing device through direct-indicating rotameters and is manually adjusted by needle valves. The combined contained metal volume of the fluxing device and filter is approximately 20,000 lb, and all chemical and metal cleanliness analysis is open loop and off-line. No on-line control is used throughout the system. Obviously, a system of this type is not commensurate with the objectives of a FIMS.

A flexible system had to be developed that not only performed the traditional purification and filtration operations but also controlled metal chemistry on a real-time basis. All of the operations originally executed in batch mode (over a period of hours in the furnace) would have to be accomplished in a dynamic state, with a total system metal residence time of minutes. The need for real-time information and the complementary process control in this case is self-evident.

The in-line system having these capabilities is illustrated in Figure 4-5. Furnace metal chemistry is fed forward to be used as initial conditions for the fluxing and alloying devices. As a cast proceeds, the characteristics of these devices are dynamically adjusted to provide the goal-state alloy chemistry, which is monitored continuously. Filtration is accomplished by a low-contained-metal volume adjustable-performance





level control devices supervised by a second-level controller, but the entire metal treatment system becomes part of the global FIMS, controlled by a higher-level executive control. Obviously, the FIMS can be incorporated as a manufacturing cell of a fully integrated aluminum production facility.

## ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI), as distinct from conventional numerical processing, is generally acknowledged to consist of two domains. The first domain encompasses natural language processing, which applies to process control primarily through operator interfacing.

AI expert systems have two major applications to metals processing control. The first application is the global coordination, scheduling, and regulation of the elementary operations of a processing system at the supervisory level. The second use of AI in metals processing control is the local regulation of a critically sensitive complex process. This is particularly true when the process is not well characterized by explicit models or the principal process variable sensors are unavailable. The aluminum ingot casting example presented earlier required a human operator who applied heuristics (rules that were formulated through years of casting experience). Unfortunately, one cannot rely on the consistent and correct application of these rules by the operator. The use of an expert system that anthropomorphically applies the heuristics is a viable control alternative, in addition to the two non-AI solutions presented in the example.

As of this writing, AI has not demonstrated the ability to make a significant impact on process control.

## REFERENCES

- Coughanowr, D. R., and L. B. Koppel. 1965. Process Systems Analysis and Control. New York: McGraw Hill.
- Gilbert, R. A., and J. A. Llwelllyn. 1985. Programmable Controller: Practice and Concepts. Rockville, Maryland: Industrial Training Corporation.
- Jablonowski, J. 1986. Advantages of Phasing in an FMS in Measured Steps. American Machining and Automated Manufacturers, 131(4):69-72
- Koff, B. L. 1984. Designing Durability in Fighter Engines. ASME Paper No. GT174, presented at the 19th International Gas Turbine Conference and Exhibit, Amsterdam, The Netherlands.
- Mamalis, A. G., and N. G. Bilalis. 1986. Flexible manufacturing systems in metal forming. J. of Appl. Metalworking, Vol. 2, No. 2, pp. 130-142.
- National Materials Advisory Board. 1986. Automated Nondestructive

Characterization and Evaluation in Metal and Ceramic Powder Production. Report Numbers NMAB-442 and MLT TR 86-34 (limited distribution). Watertown, Massachusetts: U.S. Army Materials Technology Laboratory.

Postier, R. A. 1985. Factory automation for composite structures manufacturing. SAMPE Quarterly, Vol. 16, No. 3, pp. 45-49.

Yang, B., and L. J. Lee. 1986a. Process control of polymer extrusion. Part I: Feedback control. Polymer Engineering and Science, Vol. 26, No. 3, pp. 197-204.

Yang, B., and L. J. Lee. 1986b. Process control of polymer extrusion. Part II: Feedforward control. Polymer Engineering and Science, Vol. 26, No. 3, pp. 205-213.

## Chapter 5

### SENSING

Metals increasingly can no longer be treated simply as commodities; like many other materials, they should be considered "bundles of properties." These properties determine the performance limits of the material and often the value of manufactured products. Certainly, at the conclusion of the processing sequence one can sample the product and test it to ensure the attainment of specified property combinations. However, materials science teaches that there is a direct correlation between the properties of a metal and its structure (i.e., its microstructure and composition, both of which are managed through processing). It is increasingly the role of sensors to measure process variables so that they can be controlled in real time in such a way as to attain microstructural and compositional goals and thereby ensure compliance with performance specifications. This is the essential feature of on-line process control. It is now becoming recognized that sensing and controlling (even rigidly) process variables alone does not assure a singular microstructure. Variability in raw materials and other stochastic phenomena combine to cause microstructure variations, which then result in wide bands of property combinations. To combat this, sensors are needed to directly probe the microstructure. This represents a significant challenge to measurement science, given the often extreme process environment and the need to not interfere with the process itself.

In Chapter 3, on-line process control was defined as the effective integration of sensor output with process understanding. How to adjust process variables, in the light of raw materials variations, to attain a more singular microstructure promises to be one of the most important challenges to materials processing in the next decade. In this regard it is imperative that sensing be viewed in the context of a complete control strategy. One must choose to measure only that which can be interpreted by the process model, since otherwise it is possible to be overinformed and still be unable to control the process.

### FUNDAMENTAL QUANTITIES

Fundamental quantities span the range from process variables through the microstructural characteristics to the finished product. In primary extraction, the quantities of interest are chosen from the state

variables: pressure, temperature, and chemical potential (composition), along with kinetic variables describing the rate of application of the external driving force. For example, a process model of aluminum electrolysis might require a knowledge of current density. In secondary processing, where the metal is undergoing either dimensional change or microstructural modification, the quantities of interest include the state variables and kinetic variables along with a number of dimensional and microstructural variables. Microstructural characteristics include size, size distribution, shape and orientation of grains, phases, and defects such as voids and inclusions. For example, how does one represent numerically a grain size distribution?

Quantities of critical importance are determined by the process model. Ideally, only these quantities should be measured. In cases where there is no fully satisfactory process model, another approach must be adopted; this is discussed later.

With the proliferation of sensors and with the marked decrease in the cost of computer equipment in recent years, there is the temptation to measure everything possible in order to achieve "full instrumentation" of the process. However, it is important to distinguish between sensing and control. One of the popular misconceptions about process control is that the more sensors one employs, the better one controls the process. This is not the case. Indeed, in the absence of an adequate understanding of the process, collecting and processing superfluous data may serve only to tax the information processing and control systems of the plant without offering any improvement in productivity.

## PRINCIPLES OF MEASUREMENT

A sensor is a device that detects or measures some physical or chemical quantity and converts the measurement from one signal domain to another, typically electrical. Thus it is by an energy conversion process that a sensor delivers information about the system. In the measurement and control field, the sensor is known by the term input transducer. In measurement and control the input transducer is the first element of an information collecting and processing system consisting of an input transducer, a modifier, and an output transducer. In the output transducer the electrical signal is converted into a form that can either (a) be perceived by human senses (usually visual or aural), in which case the device is termed a display, or (b) cause some physical change in the process (e.g., open a valve or throw a switch), in which case the device is termed an actuator. To drive an actuator requires that the information from the sensor be interpreted in accordance with a process model. This occurs in the modifier, which also conditions the output from the sensor by signal processing techniques. The future feasibility of process control systems such as this is frequently perceived to be limited by peripheral components of the system, such as sensors. For materials processing, this is especially so, but there also exists a pressing need for the development of deterministic process models capable of interpreting sensor data and restructuring a process trajectory to bring a microstructure back within bounds.

To classify the large number of available sensors and to identify potential new sensors, it is convenient to examine the field of sensors in the context of the types of probing energy available and the ability to relate this to the process and microstructure variables to be measured. Lion (1969) has distinguished six probe energy forms, as shown in Table 5-1. By considering the energy forms of the signals at the input and output stages of a sensor (for all practical purposes the output is electrical), Middelhoek and Noorlag (1981/82) have summarized in matrix form the physical and chemical effects that can be used in sensors (Figure 5-1). Table 5-2 lists some sensors and the principle of operation in terms of the relevant effect. Some sensors generate electrical output without an auxiliary source of energy (e.g., a thermocouple or a pH meter) and are termed self-generating transducers. Other sensors can convert input energy forms to electrical energy only with the aid of an auxiliary energy source (e.g., a strain gauge or a magnetoresistor) and are termed modulating transducers.

TABLE 5-1 Six Groups of Signals With Examples

Radiant signals	Intensity, wavelength, polarization, phase, reflectance, transmittance, force, pressure, torque, vacuum, flow, volume, thickness, mass, level, position, displacement, velocity, acceleration, tilt, roughness, acoustic wavelength and amplitude
Mechanical signals	
Thermal signals	Temperature, heat, specific heat, entropy, heat flow voltage, current, charge, resistance, inductance, capacitance, dielectric constant, electric polarization, frequency, pulse duration
Electrical signals	
Magnetic signals	Field intensity, flux density, moment, magnetization, permeability, composition, concentration, reaction rate, toxicity, oxidation-reduction potential, pH, pollutants
Chemical signals	

Figure 5-2 shows the various types of sensors in a three-dimensional diagram (Middelhoek and Noorlag, 1981/82). For self-generating transducers, the x-axis represents the form of the input signal energy, the y-axis the form of the output signal energy, and the z-axis the form of the modulating signal input. For example, when only electrical auxiliary energy sources are considered, five different input transducers (sensors) and five different output transducers can be distinguished. The modulating input transducers are based on photoconductance, piezoresistance, thermoresistance, magnetoresistance, and electrical conductance effects.

In \ Out	Rad.	Mech.	Thermal	Electrical	Magn.	Chem.
Radiant				Photovoltaic effect Photoconductivity Photomagnetolectric effect Photoemissive effect		
Mechanical				Piezoelectric effect Piezoresistance Triboelectric effect		
Thermal				Seebeck effect Thermally sensitive resistivity Pyroelectric effect Thermodielectric effect		
Electrical				---		
Magnetic				Hall effect Phys. magneto resistance Geom. magneto resistance Suhl effect		
Chemical				Galvanoelectric effect Electrolytic conductivity Chemoelectrification Impurity-sensitive resistivity		

FIGURE 5-1 Physical and chemical effects for input transducers.

TABLE 5-2 Transducers and Effects

Energy Domains	Transducer	Effect
Radiant	Solar cell; photodetector	Photovoltaic effect; photoconductance
Mechanical	Pressure cell; piezotransistor	Piezoresistance; piezoelectric effect; piezjunction effect
Thermal	Thermocouple; thermoresistor	Seebeck effect; thermally sensitive resistivity
Magnetic	Hall plate reproducing head	Hall effect magnetoresistance
Chemical	pH-meter galvanic cell	Chemovoltallic effect; Volta effect

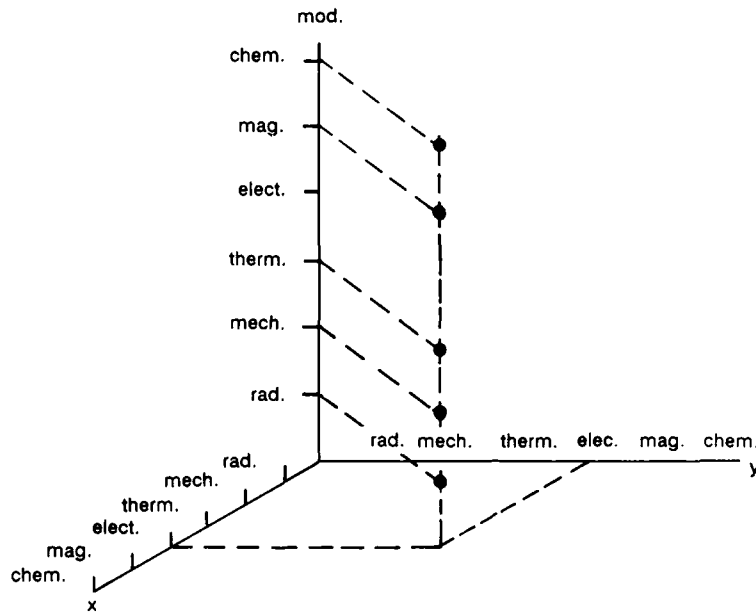


FIGURE 5-2 Three-dimensional transducer diagram showing the five possible modulating input transducers based on photoconductance, piezoresistance, thermoresistance, magnetoresistance, and electrolytic conductance effects.

To this point the discussion has attempted to categorize the types of sensors on the basis of the forms of energy. Equally important is the consideration of the magnitude of energy, for this determines the sensitivity of the device. Table 5-1 presented six forms of energy available for use in sensor applications. So-called radiant signals, electrical signals, and magnetic signals can be ranked on the basis of their position in the electromagnetic energy spectrum, shown in Figure 5-3.

The usefulness of any form of radiation in a given application is limited by response time and spatial resolution. The frequency of the radiation determines its response time, and the wavelength of the radiation determines its spatial resolution.

In the measurement of chemical composition, the sensitivity of the technique is determined by the quantum energy of the probe radiation, which must exceed a critical value of energy as defined by the effect employed to detect the chemical species. The critical energy can be a bond energy as in Raman spectroscopy or an electronic binding energy as in x-ray fluorescence. These relationships apply equally well to particle beam radiation, such as electrons in electron microscopy or neutrons in neutron activation analysis.

Mechanical signals can also be ranked in a similar fashion, but on the basis of their position in the mechanical energy spectrum (Figure 5-4), which spans the range from direct contact through ultrasonics. Unlike the electromagnetic energy spectrum, the mechanical energy spectrum has an upper limit, which in solids is given by the Debye frequency. In fluids

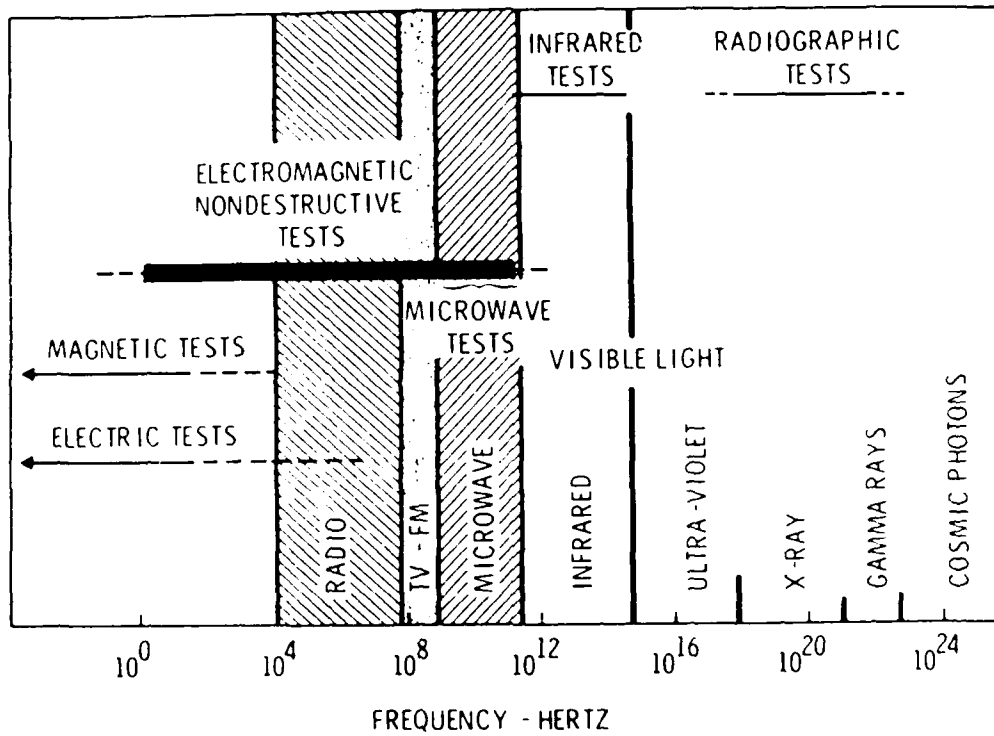


FIGURE 5-3 The electromagnetic spectrum (Libby, 1971).

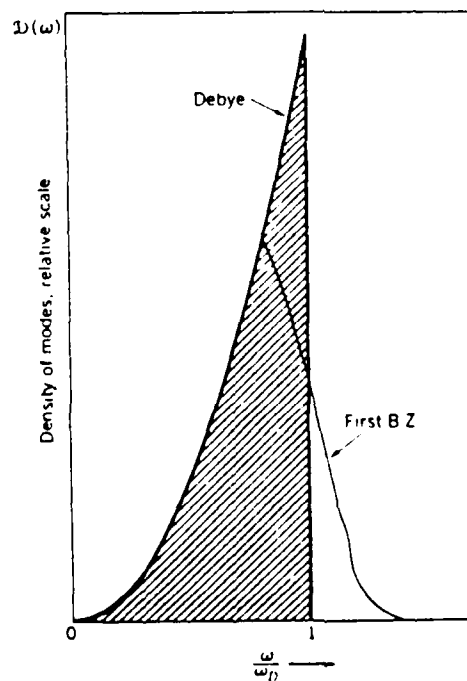


FIGURE 5-4 Density of modes  $D(\omega)$  versus  $\omega$ , with assumed constant phonon velocity, for integration in  $K$  space over the Debye sphere (shaded area) and over the cube that forms the first Brillouin zone of a monatomic simple cubic lattice (Kittel, 1971).



there is a corresponding quantity, typically estimated by  $kT/h$ , the product of the Boltzmann constant and temperature divided by the Planck constant.

The measurement of temperature is less straightforward. While there is a spectrum of thermal energy shown in Figure 5-5, to use it in temperature measurement requires a knowledge of emissivity, itself a function of temperature. Indeed, this is one of the central problems in optical pyrometry.

The discussion of microstructural characterization is aided by Figure 5-6, which shows the range of physical dimensions of concern in metals processing. Figure 5-6 spans nanostructure, microstructure, and millistructure, and extends to manufacturing dimensions or macrostructure. (For historical reasons, the study of macrostructure--i.e., accurate determination of product dimensions--is termed metrology. However, the following comments apply regardless of the absolute size of the feature under study.) As mentioned earlier, spatial resolution is governed by the wavelength of the interrogating signal--in particular, by the relative magnitudes of the effective wavelength of the probe signal (radiant or mechanical) and the size of the microstructural feature. One can observe either a facsimile image or a diffraction image. For particle beams and mechanical energy, the effective wavelength is given by the deBroglie relationship,  $\lambda = h/p$ , where  $\lambda$  is the effective wavelength,  $h$  is the

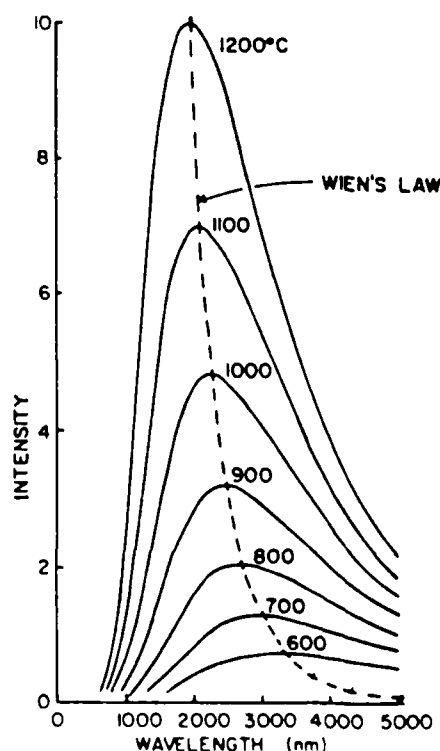


FIGURE 5-5 Blackbody curves for different temperatures showing the displacement of the maximum according to Wien's law (Nassau, 1983).

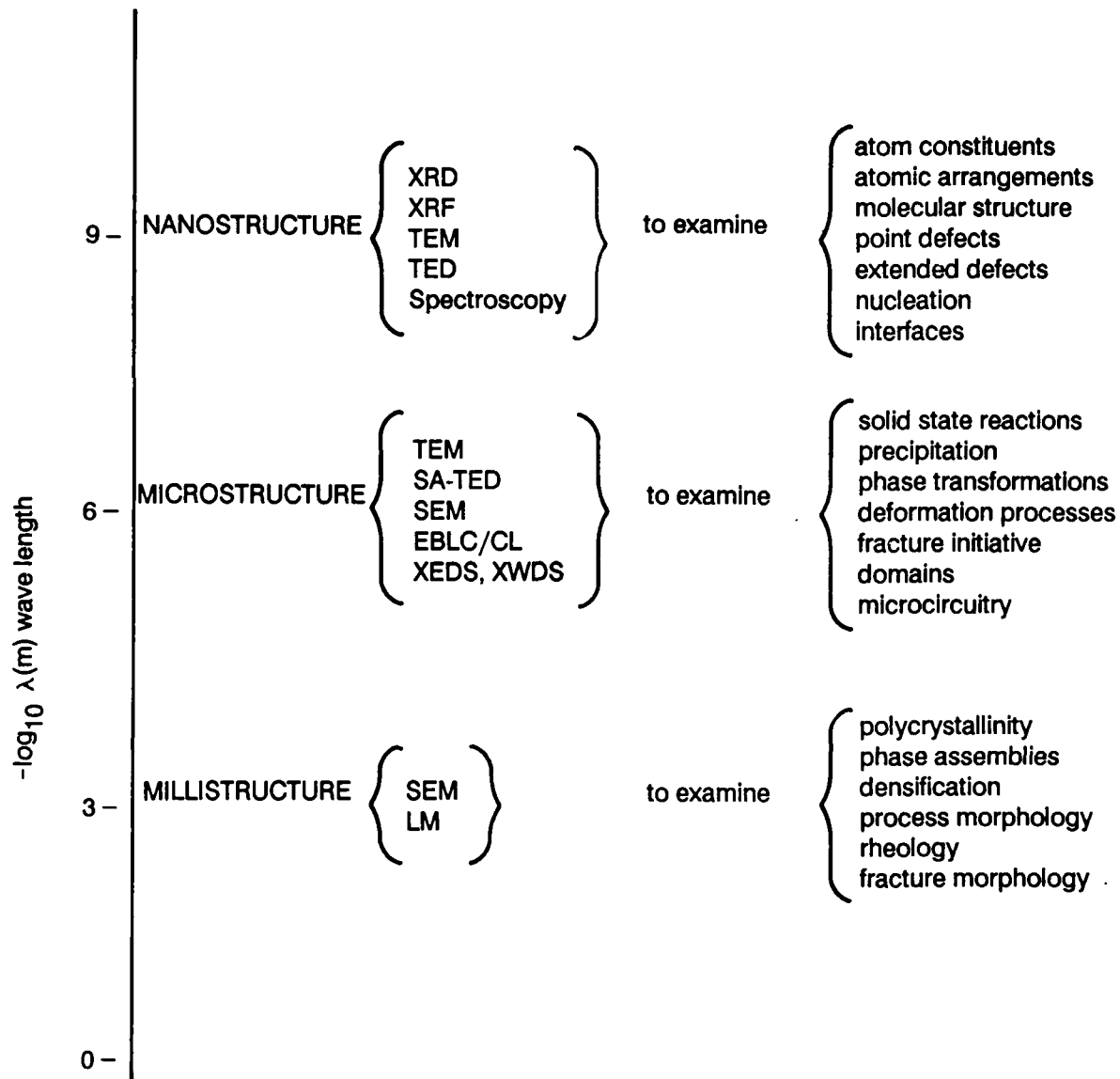


FIGURE 5-6 Scale of microstructure and associated NDE tools.

Planck constant, and  $p$  is momentum. Figure 5-7 compares some contemporary analytical instrumentation in the light of the foregoing (Kossowsky, 1983). The rule governing spatial resolution in microstructural analysis applies equally well in describing the sample spot size in chemical analysis.

In the investigation of very fine structure at the scale of atomic dimensions, one discovers that spatial resolution becomes limited by the Heisenberg uncertainty principle and the requisite particle velocities assume relativistic proportions. The same holds for the chemical analysis

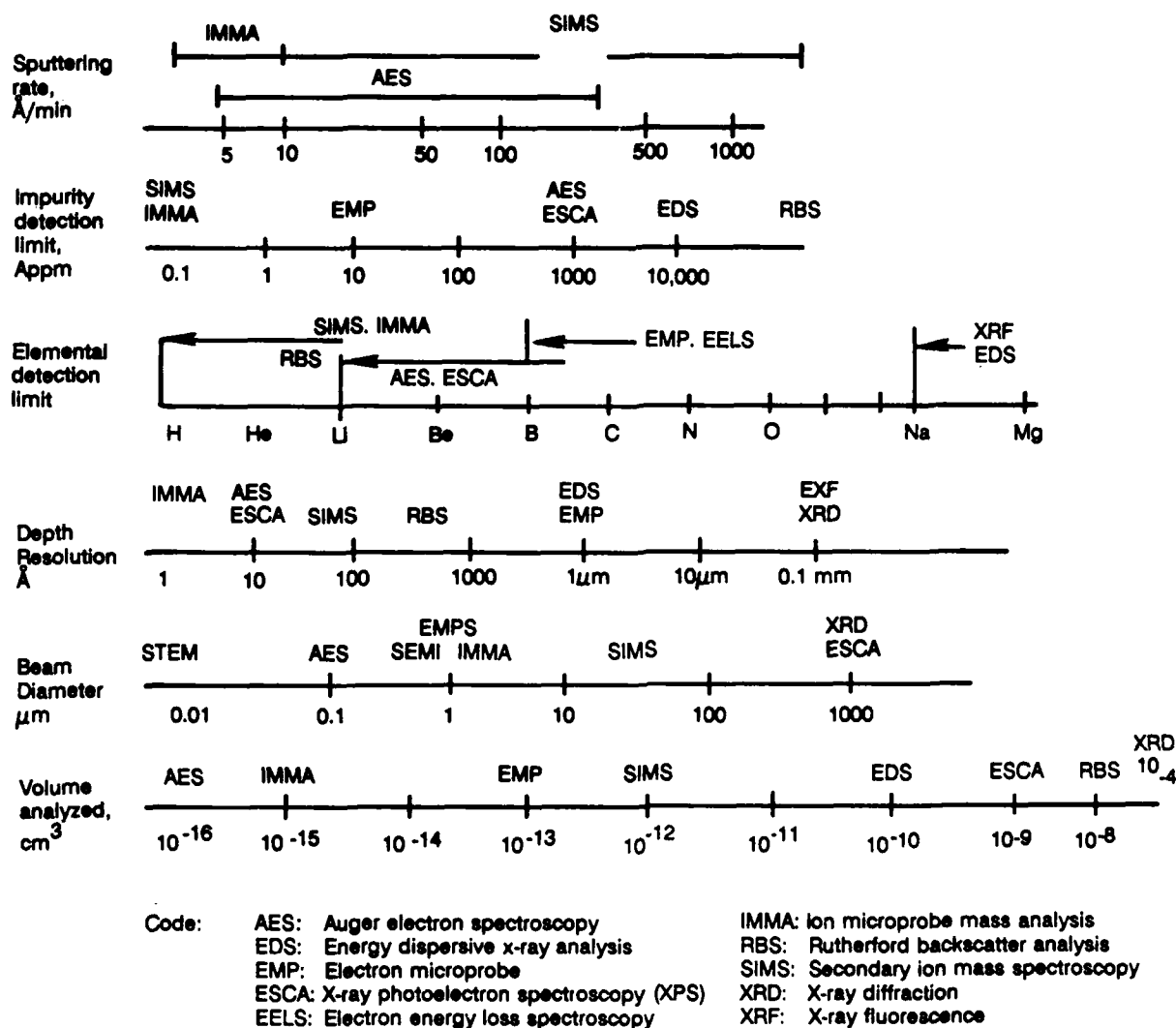


FIGURE 5-7 Comparison of various analytical methods.

of species with very tightly bonded electrons such as elements of low atomic number.

Thus far the fundamental quantities and their principles of measurement have been listed. However, in many instances the properties of a metal and, therefore, the compliance with performance specifications can be assessed very effectively by measuring what, for lack of a better term, will be referred to here as secondary, derived, or indirect quantities. Examples of the kinds of measurements performed in this regard include eddy current and electrical conductivity measurements (electrical properties), magnetometry and Barkhausen noise (magnetic properties), ultrasound (elastic properties), and optical absorption and scattering (optical properties). There are many other materials characteristics that can be taken as indicators of quality. These include

dielectric properties and thermal properties. In all cases, however, the sensors performing the measurements are bound by the limitations enunciated here because these limitations are not based simply on subjective evaluations of today's best technology but rather on the laws of physics as applied to metallic matter. This is extremely important in the appraisal of new sensor technologies. There are other considerations as well:

First, the sensor ideally should not perturb the subject under investigation. Obviously, the preferred form of sensing is noninvasive. Some processes do not lend themselves to this form of monitoring, and alternatives should be selected with the intention of causing the least disturbance.

Second, in choosing or designing a sensor one must consider the time to make a measurement as compared to the response time of the process (i.e., the physical inertia of the system). The response time of the system can be determined empirically; however, with the aid of a process model, changes in relation to process inputs can be easily predicted. The time to make a measurement is the sum of the response time of the sensor, which is limited by the criteria already noted, and the time to process the sensor output data. One then must consider the time constant of the process versus the time constant of the information about the process. There is a need to balance all these factors. There is no point in installing highly responsive sensors to monitor a process that itself cannot be quickly adjusted. Likewise, there is no point in using a sophisticated process model that requires computational time exceeding the physical time constant of the process.

Third, sensors for metals processing in many cases must be employed in hostile environments--high temperatures, extreme chemistries (highly oxidizing, highly reducing, corrosive), electromagnetic interference. This raises two issues. The first is obvious: Sensors for these environments must be robust. This means that as sensor manufacturers begin to design very sensitive devices based on phenomena producing only subtle changes, attention must be given to these environmental challenges. The second is the issue of reliability. This goes beyond simply making the sensor robust. One must be concerned that the sensor is neither broken nor gradually drifting off calibration. This argues for sensors that can detect such malfunctions and report them to the control system.

#### SENSOR-MEDIA INTERACTION MODELS

The sensors sought for controlling materials processing produce electrical signals resulting from interactions between the sensor and material. These signals are the combined responses of the material and sensor. Passive sensor systems rely on the material itself to generate the energy source (e.g., optical pyrometers or acoustic emission) that is subsequently sensed. Active sensors (e.g., those based on ultrasound) generate a probe signal and measure its character after interaction with the material. For both types of sensors, it is essential to clearly understand the processes by which sensing is achieved so that optimum sensor designs may be achieved and the fullest use made of the data.

The phenomena for many traditional sensors such as pyrometers, thermocouples, pressure sensors, and thickness gauges are based on classical physical phenomena such as optical emission (Wien's displacement law), the Seebeck effect, the piezoelectric effect, and x-ray absorption. Extensive modeling is not needed. That already available can be utilized to optimize sensor performance for specific applications.

The need for sensors capable of probing microstructure variables, however, is leading to the development of active sensors based on ultrasound and eddy current principles and passive acoustic emission techniques. The operation of these sensors is based on less-well-developed physical concepts. Sensor development is dependent on continued advancement in understanding of sensor-media interactions. In addition, progress in this field will occur from fusion of data from multiple sensors used in application-specific situations. Because of the many varied interactions between sensors and the metal being processed, sensor modeling needs to be carried out via supercomputers.

## EMERGING SENSORS

Without better sensor systems, there can be no real advancement in process control, and without the advancements of in-process control, there can be no significant advancement in the processes themselves. The development of sensors is often complicated by lack of a knowledge base; the relationships between sensing mechanism, measurement, and microstructure are yet to fully emerge. Furthermore, the hostile environment in which sensors are used, the limited time available for measurements, and the need to avoid interference with the process itself all introduce constraints on practical sensor systems that ultimately result in less-than-ideal data. Thus there exists a need to develop better models and algorithms of sensor-material interaction, both for the analysis of collected data and to reduce the data into a useful form (Mehrabian and Wadley, 1985; Horvath, 1985). The interplay between these factors can best be appreciated by examining a selection of emerging sensors based on optical detection, ultrasound acoustic emission, and eddy currents.

The examples cited below are derived in part from National Institute of Standards and Technology and American Iron and Steel Institute work, as they are representative of recent developments. New sensor technology is an active field and many others equally interesting could be noted. It is our intent here to give examples and not try to be comprehensive.

### Optical Sensors

#### Surface Defect Sensor

The surface quality of steel and aluminum sheet is very important both to the producers and to the users of these materials. Optical reflectivity has been used successfully for the surface inspection of slowly moving sheet for off-line quality control purposes (Horvath, 1985; Wayne-Norton et al., 1977). However, its slow speed in the past has meant that only a sample of strip is inspected. Thus conditions that cause surface imperfections can go undetected for extended times. Real-time (in

the loop) determination of surface quality prior to the coiling of processed strip is extremely difficult because of the very high strip speeds (up to 2000 m per minute) and the wide variety of imperfections that may occur. These imperfections must be both distinguished from benign blemishes and characterized so that their source may be inferred and appropriate steps taken for their timely elimination (Mehrabian et al., 1982). In one development effort, the AISI is coordinating a collaborative program funded by a consortium of steel and aluminum producers to develop a sensor for this need.

Research is based on a coherent light-scattering approach, as shown in Figure 5-8. An intense collimated laser beam is rapidly scanned across the width of the moving metal strip. Photodetector arrays are positioned across the strip width at angles to the strip predetermined to optimize the defect scattering (the signal) to background scattering (noise) ratio. Ensuring acceptable signal:noise ratio for defects of importance is a key feature of the sensor concept under development. Varying the optical wavelength and detector angle are the principle ways for enhancing signal:noise. The voltage outputs of each detector are continuously digitized, recorded, digitally processed, and then subjected to pattern recognition and other digital signal analysis techniques to detect and characterize defects. This condensed information can be electronically stored for each coil so that quality can be numerically catalogued.

Even for sensor concepts that yield acceptable signal:noise, the combination of high strip speeds and many different types of imperfection combine to pose major problems in high-speed data acquisition and digital signal analysis. For example, to fully inspect a 2-m-wide strip moving at 30 m per second (5900 ft per minute) with a 1-mm laser spot size requires state-of-the-art 8-bit digitization rates of 200 MHz. Digital signal analysis of these very dense data streams is too slow, even with today's most advanced computers, and preprocessing of the data is therefore essential if the sensor is to remain in the control loop. Only then can pattern recognition and other AI software be used to characterize the defects from the condensed data. Software alone cannot solve this aspect of the problem, however. Data preprocessing may also be too slow, or may filter out desirable signal traits. Devising sensor measurement methodologies that simplify the preprocessing and defect characterization algorithms is a critical factor in the successful development of this sensor.

#### Particle Size Determination

In a previous study (National Materials Advisory Board, 1986) the current status of advanced metal and ceramic powder production was addressed. The report identified the opportunity for computer-based process control scenarios, provided new sensors for continuous determination of powder particle size could be developed. The report assessed the potential of a number of light-scattering approaches. Subsequently, research at the National Institute of Standards and Technology has begun an experimental assessment of candidate light-scattering sensors on its gas atomization facility. These include a commercially available laser

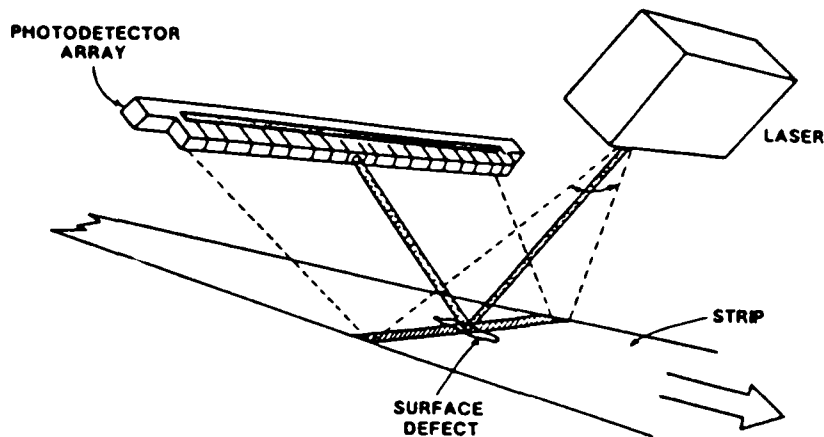


FIGURE 5-8 Schematic illustration of surface defect sensor.

diffraction particle sizer as well as emerging light-scattering technologies such as polarization ratio scattering and laser Doppler velocimetry.

The intent is to develop an optimum combination of sensors and process models so that atomization phenomena (jet instabilities, ligament rupture, etc.) occurring within the atomizing die may be controlled by adjusting process variables such as gas pressure and liquid stream temperature so that an optimum particle size distribution is attained. Research both at National Institute of Standards and Technology and at the Naval Research Laboratory is also utilizing high-speed photography outside the control loop, to gain deeper insights into the fundamentals of the atomization process itself as a further input to process model development.

Interest is intensifying in this area with the realization that on-line control of the particle size distribution facilitates control of particle undercooling and thus control of the fractional distribution of metastable phases. The ability to control and even change the volume fraction of metastable phases within the particle stream both enhances the productivity of conventional powder atomization and creates exciting new opportunities for subsequent near-net-shape processing.

#### Molten Metal Composition Sensor

Basic metals production could be significantly improved with the availability of a sensor capable of real-time chemical analysis of molten metals and alloys (Mehrabian et al., 1982). In an AISI collaborative program, Y. Kim and coworkers at Lehigh University are exploring the use of an in situ transient emission spectroscopy approach (Y. Kim, private communication).

In this approach, an intense laser pulse is used to evaporate and then electronically excite a small representative sample of the alloy within the melt (Figure 5-9). The plasma thus created subsequently decays back to the ground state by the same photon emission processes traditionally utilized for emission spectroscopy analysis. The electromagnetic emission is collected and transported to a high-speed spectrum analyzer, where the intensity of individual lines in the emission spectrum is used to rapidly infer the chemical composition.

A key aspect of the approach concerns the degree to which the composition of the ablated material in the plasma is truly representative of the bulk composition. For instance, it obviously should not be heavily contaminated by slag. A more insidious problem is the potential for selective enrichment of the vapor by the more volatile elements present in the sample. The use of very brief, very high-intensity laser pulses and careful calibration shows promise of overcoming this problem.

### Ultrasound Sensors

#### Surface Modification Sensor

Localized surface hardening is a method used increasingly frequently for enhancing resistance to wear and fatigue (Kear et al., 1979). Carburization and nitriding have been used for many years for this. More recently, directed high-energy beams (laser or electron beams) with energy densities of  $10^3$  to  $10^4$  Wcm<sup>-2</sup> are swept over the surface, causing transient local heating and subsequent rapid cooling back to ambient (Elkind et al., in press). This can produce surface melting, alloying, or enhanced dissolution of alloy elements, resulting in a surface-hardened layer. The depth and hardness of the surface modification need to be determined for all these processes so that they may be controlled in-process to produce an optimal surface modification. At present, no feedback control exists, and adequate quality is assured through destructive tests of sample specimens.

Measurement of the ultrasonic surface wave velocity as a function of frequency (i.e., the surface wave dispersion) is one method being explored to characterize depth-varying properties (Elkind et al., in press). Surface (or Rayleigh) waves have the special feature that their amplitude decays rapidly with distance below the surface on which they propagate. Furthermore, the rate of decay is scaled by the ultrasonic wavelength. Short-wavelength waves decay rapidly beneath the surface and therefore propagate at a velocity controlled by near-surface elastic properties. Long-wavelength waves decay more slowly with depth and thus propagate at a velocity controlled by a combination of surface and substrate elastic properties.

Thus, as one increases the wavelength of a probe wave, a critical wavelength is reached where the velocity starts to change as the wave begins to sample unmodified material beneath the depth of modification (between 0.8 and 1.0 mm) (Figure 5-10). Furthermore, the difference in the long- and short-wavelength velocity limits is a good indicator of the hardness of the surface-modified layer itself. The emergence of non-contact electromagnetic acoustic transducers (Morris and Keener, 1986)



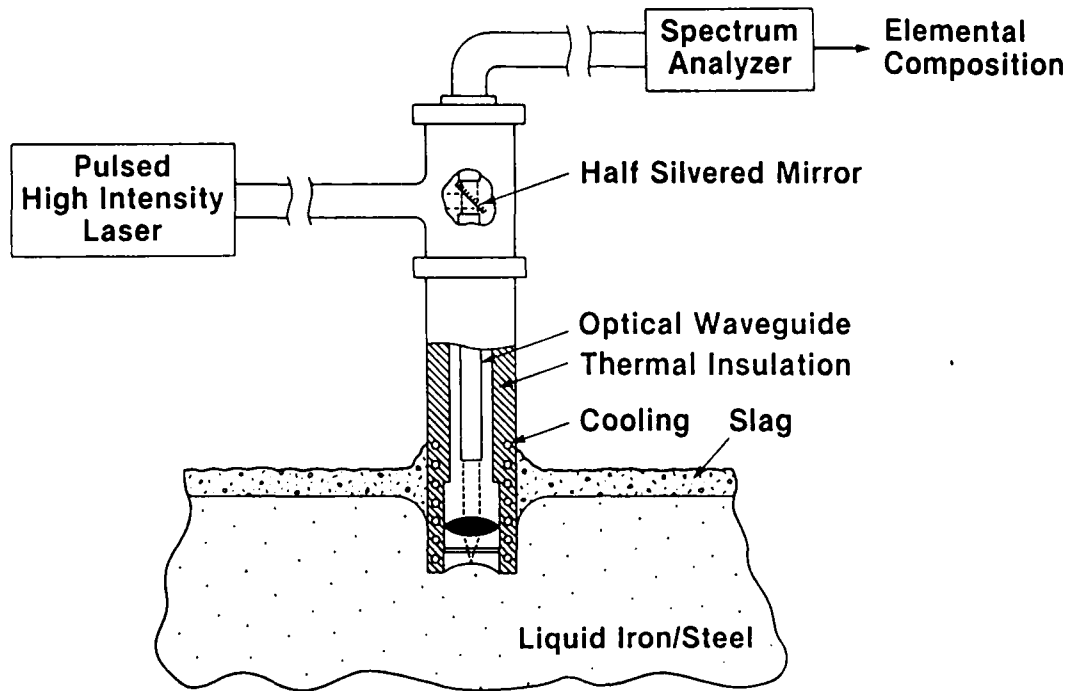


FIGURE 5-9 Schematic illustration of the laser chemical composition probe being developed for liquid metal analysis (Horvath, 1985).

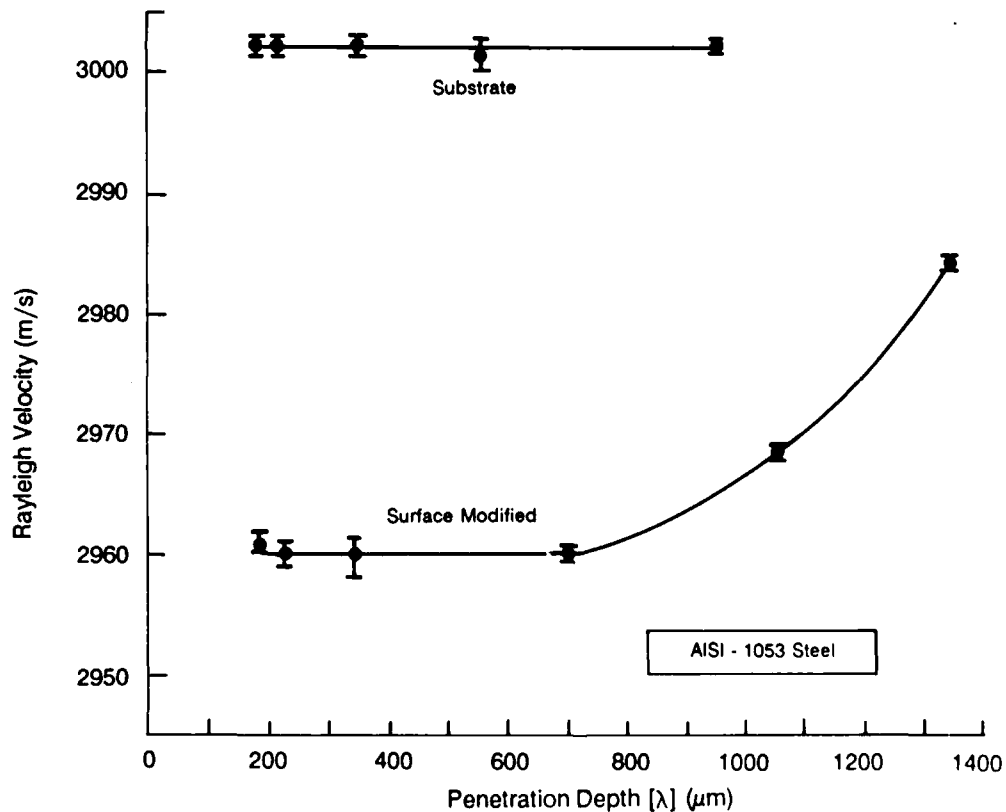


FIGURE 5-10 Dependence of Rayleigh wave velocity on wavelength ( $\lambda$ ) for a surface subjected to electron beam modification and for the unmodified surface (substrate) (Elkind et al., in press).

promises a means for nonintrusively making these measurements during processing. Better inverse algorithms for determining layer properties from wavelength velocity relations are, however, needed to improve the accuracy of the approach.

#### Molten Metal Inclusion Sensor

The elastic constants and density of inclusions in molten alloys are different from those of the molten alloy itself. They thus have a different acoustic impedance than liquid metal. The difference in acoustic impedance of the inclusions results in scattering of incoming elastic energy waves. The intensity of the scattering is affected by ultrasonic frequency and is especially strong as the wavelength approaches the inclusion dimensions. For inclusions in the range from 0.1 to 1.0 mm, maximum scattering occurs in the 1- to 3-MHz range. Since other scattering processes for liquid metals are weak, the scattering from inclusions can readily be measured and provides a convenient means for both detecting the number of inclusions present in a molten alloy and (by varying ultrasonic frequency) estimating their size.

Mansfield and Bradshaw (1985) have developed a sensor based on this principle for aluminum alloys. Their sensor consists of two flat parallel titanium plates that are fully immersed in the liquid metal. An ultrasonic pulse is applied to one plate; the reverberations between the plates are monitored. When large numbers of inclusions are present, energy is scattered out of the forward-propagating ultrasonic pulse, and the reverberations rapidly ring down. By measuring the attenuation of the transmitted beam at a fixed frequency (typically in the range from 5 to 10 MHz) it has been possible to assess the melt cleanliness.

This ultrasonic approach is probably equally valid for other metals and alloys, including steels and superalloys containing inclusions and/or ceramic particles. The higher temperatures involved pose significant practical problems for ultrasonic generation and detection, but they may well be amenable to solution, especially given the recent availability of laser-generated ultrasound (Birnbaum and White, 1984) and noncontact high-temperature electromagnetic acoustic transducers (Alers and Wadley, 1987).

#### Internal Temperature Distribution Sensor

As indicated earlier, an internal temperature sensor is needed to image the temperature field within solidifying alloys so that solidification processing may be better controlled. If a body's interior is probed with a penetrating radiation and a temperature-dependent physical property is measured, then the temperature itself may be detected. Ultrasound is one potential probe radiation under study, and ultrasonic velocity is a measurable physical quantity that is strongly temperature-dependent (Wadley et al., in press). For many metals, the velocity of longitudinal ultrasonic waves decreases with increasing temperature at a rate between  $0.5$  and  $1.0 \text{ ms}^{-1}\text{C}^{-1}$  (Figure 5-11). The effect is largely independent of the ultrasonic frequency, and the velocity changes that are due to temperature differences are usually much

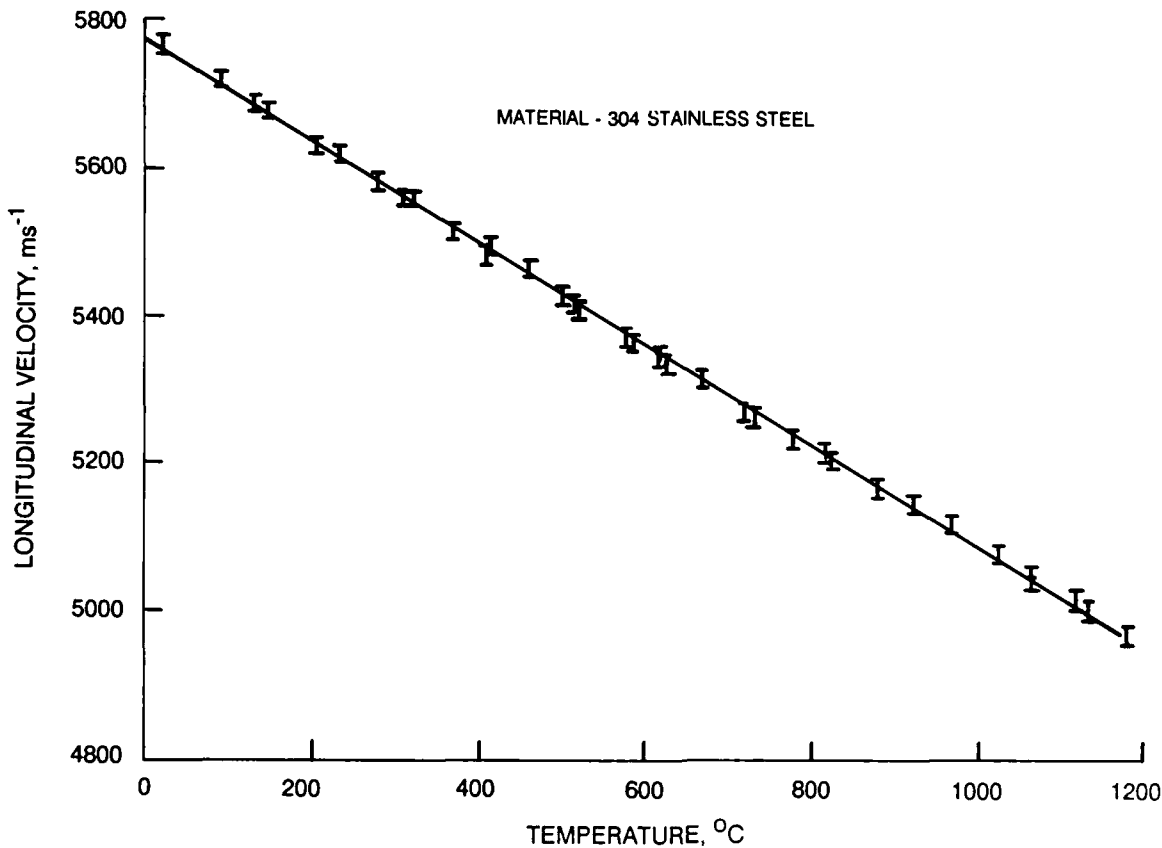


FIGURE 5-11 Dependence of longitudinal ultrasonic velocity on temperature for AISI 304 stainless steel (Wadley et al., in press).

greater than those due to microstructure variations (texture, phase distribution), internal stresses, or dislocation distributions.

One approach to internal temperature sensing involves using an intense laser pulse to generate ultrasonic signals and a high-temperature noncontact EMAT as a receiver (Figure 5-12). The time of flight (TOF) of the ultrasonic pulses along paths of known length allows measurement of the average velocity along the path. Using reference data such as that shown in Figure 5-11, this average velocity may be directly converted to the average internal temperature along the ray path.

If independent TOF measurements for propagation along different ray paths are made, tomographic-like algorithms may be used to reconstruct an internal temperature range. These algorithms, it turns out, require enormous numbers of TOF measurements if high spatial resolution is to be sought. However, it has been found that using an algorithm based on a least squares inversion procedure facilitates incorporation of *a priori* information for the reconstruction. In this particular case, the *a priori* information is a thermal model that predicts the internal temperature distribution exactly, provided thermophysical constants and initial and boundary conditions are known. In practice these are not always well defined. The TOF measurements are used in essence to determine these.

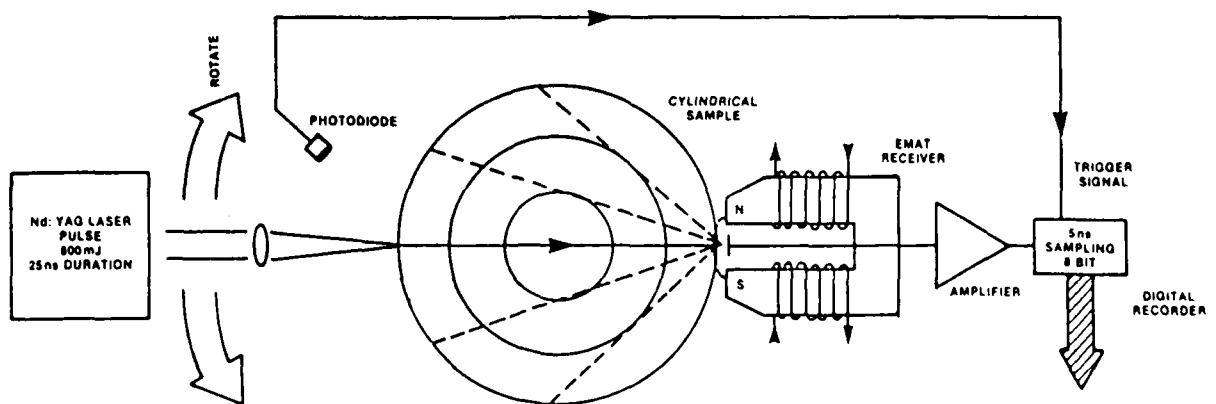


FIGURE 5-12 Schematic diagram of ultrasonic internal temperature sensor utilizing laser generation and EMAT detection.

This is done by comparing, in a least squares sense, predicted TOF values based on successive interactions of the temperature model (with adjusted boundary conditions) to the set of measured TOF values. Figure 5-13 shows the good level of agreement between such an ultrasonic (curve) and embedded thermocouple (points) measurement of temperature for a 304 stainless steel sample.

Internal temperature sensors are needed for many processes besides control of continuous casting. For example, they are needed for high-speed aluminum extrusion, single-crystal turbine blade growth, and the growth of single-crystal semiconductors. Although the ultrasonic approach under development for steel may provide a sensor development route for these other processes, the different process constraints may dictate alternative methodologies. For example, the high local stresses associated with laser generation of ultrasound, while nonperturbing to the solidification of steel, may cause highly deleterious dislocation generation during semiconductor single-crystal growth.

#### Eddy Current Sensors

Electromagnetic sensors are being developed for the measurement of impedance and physical dimensions of metallic materials during processing (Kahn and Wadley, 1986). The availability of automated high-precision impedance measuring equipment has spurred development in this area. The impedance measurement provides a method of obtaining the electrical resistivity of the test material, and, since the temperature-dependence of the resistivity can be determined, the method makes possible a noncontact measurement of temperature. Attendant to this approach is the measurement of cross-sectional area, which is equivalent to a measurement of diameter on bars and pipe.

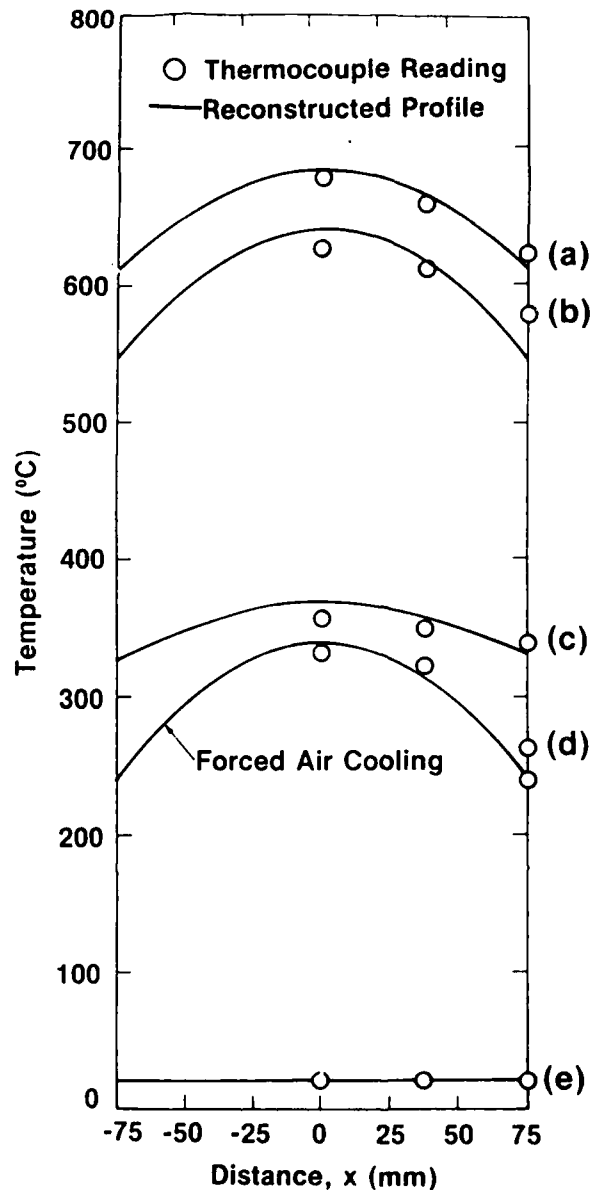


FIGURE 5-13 The internal temperature distributions reconstructed from noncontact ultrasonic measurements compared with embedded thermocouple measurements (circles) for AISI 304 stainless steel. The distance corresponds to a line through the center of a 15- x 15-cm steel billet cross section (Wadley et al., in press).

The studies on resistivity and temperature are being carried out jointly by the National Institute of Standards and Technology and the Aluminum Association, a consortium of aluminum product manufacturers. The objective of this project is the development of a sensor to be used for the control of the temperature of aluminum bar during extrusion processing. Figure 5-14 shows how on-line measurement of the temperature of the extruded rod can be integrated into a feedback system to control end material and produce optimized physical properties.

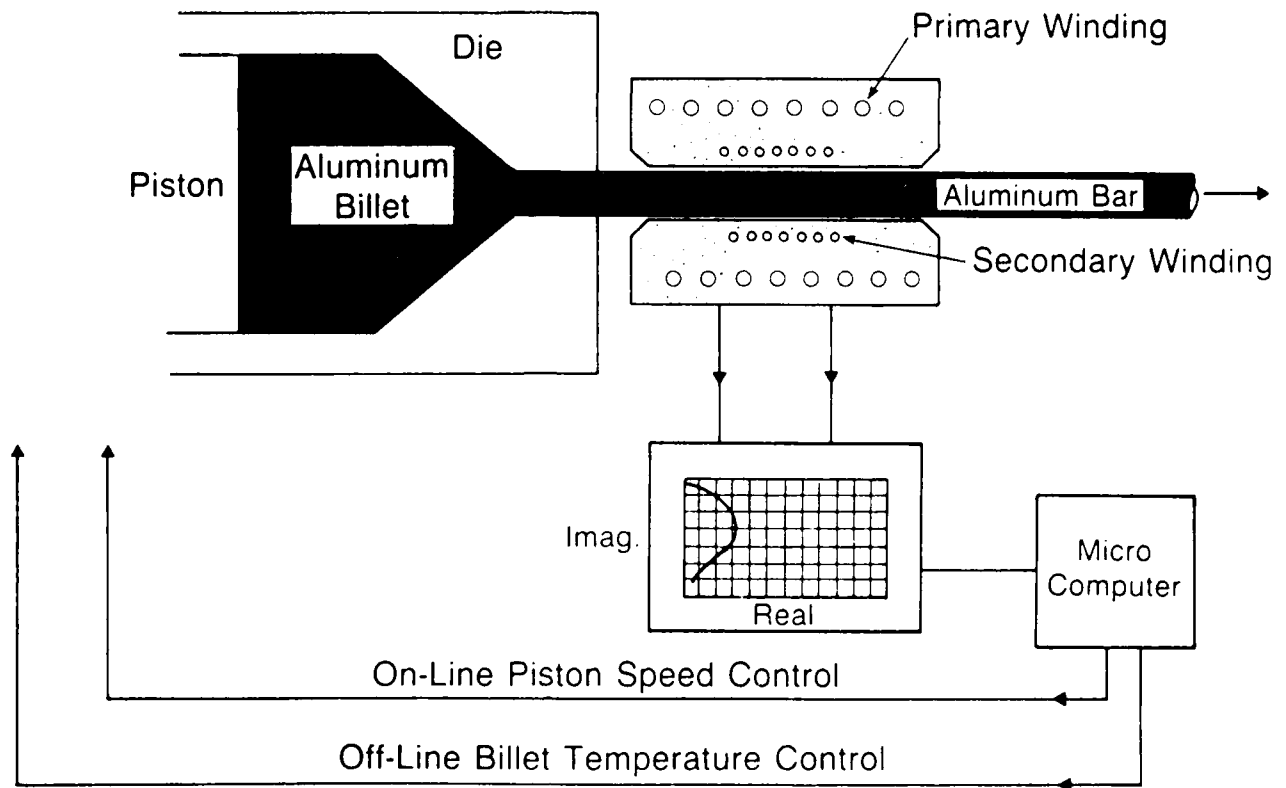


FIGURE 5-14 Proposed use of electromagnetic sensor for measuring the temperature of aluminum rod during extrusion processing.

Figure 5-15 illustrates the principle of the measurement process. The output from the oscillator of a commercial impedance/gain-phase analyzer is used to drive a power amplifier that excites a primary coil, inducing eddy currents in the test sample. The voltage induced in the secondary pickup coil, which depends on the frequency of the oscillator and on the resistivity and dimensions of the sample, is passed to the test channel of the analyzer. The reference voltage, taken from a resistor in the primary circuit, is proportional to the primary current. The analyzer computes the transfer impedance of the sensor (i.e., the magnitude and phase of the test voltage relative to the reference voltage). From this the contribution to the impedance by the sample may be extracted.

This configuration has several advantages over that of the more traditional single-coil use. The measurements are quite insensitive to changes of resistance of the coils. This provides immunity to difficulties associated with variations caused by temperature. Also, because the pickup coil can be much shorter than the primary, end effects associated with fringing magnetic fields are eliminated, simplifying the analysis. Finally, the signal-to-noise ratio at low frequencies is greatly improved through the use of an audio power amplifier for driving the primary current.

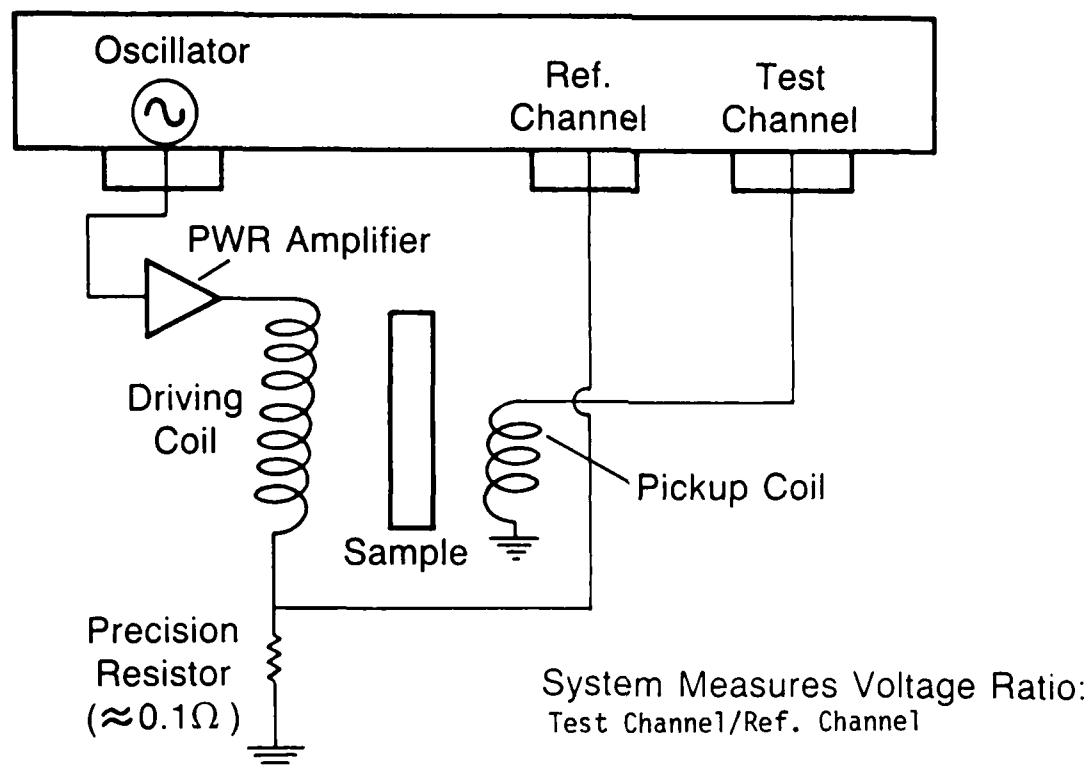


FIGURE 5-15 Schematic diagram illustrating the method of measurement of impedance. The primary (driving) coil, the secondary (pick-up) coil, and the cylindrical test sample are concentrically placed in the actual sensor.

Measured data for a 1-in.-diameter aluminum rod are plotted in Figure 5-16. The imaginary part of the impedance is plotted against the real part for all frequencies measured (400 frequencies from 50 Hz to 20 kHz). The data are traditionally normalized by dividing by the imaginary part of the impedance of the empty coils. Characteristic points on the curve are indicated by arrows. The intercept on the imaginary axis is equal to

$$1 - (\text{sample area/coil area})$$

This provides an immediate determination of the diameter of the sample. The knee of the curve, the point at the frequency of maximum eddy current loss, is related to the resistivity by

$$\sigma = 6.25 / (2 \pi \mu_0 \sigma f_0 r_s^2) \text{ ohm}^{-1} \text{m}^{-1}$$

where  $\sigma$  is the electrical conductivity (the reciprocal of resistivity),  $f_0$  is the frequency at the knee,  $\mu_0$  is the permeability of free space

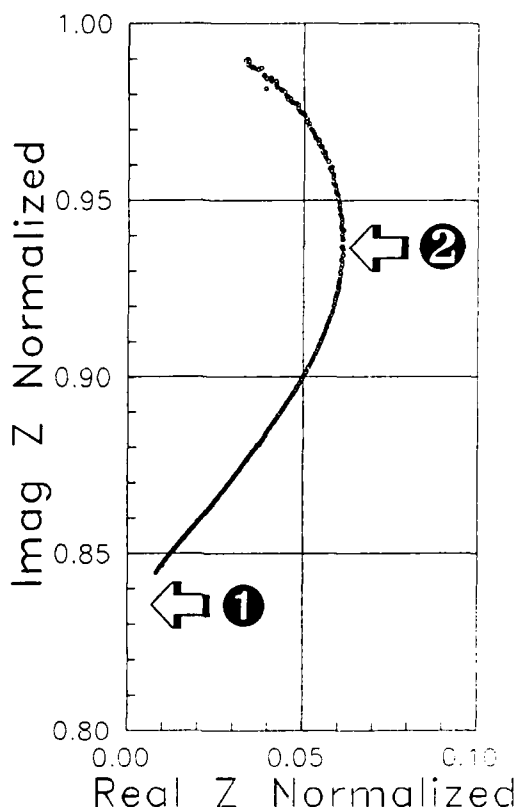


FIGURE 5-16 Impedance plot of measured test data on an aluminum rod 1 in. in diameter. Real and imaginary parts are normalized relative to the imaginary part of the empty coil impedance. Critical points are (1) the extrapolated intercept on the imaginary axis, which determines the area of the sample, and (2) the point of maximum real part (loss), which determines the conductivity-area product.

( $4 \times 10^{-7}$  H/m), and  $r_s$  is the radius of the rod under test. Thus, these two critical points yield the desired information. The correlation with temperature must then be obtained by independent measurement of the resistivity temperature-dependence for the various alloys under study.

The measurement of diameter is being applied to monitoring the sintering of aluminum alloy powders by hot isostatic pressing (HIPping). The powder to be HIPped is compressed and sealed in an aluminum tube. The two coils of the sensor are placed in the furnace, surrounding the sample, with the measurement leads passed to the outside. The impedance can be measured continuously through the process and the diameter thereby monitored and the rate of densification controlled.

Further research in this area is extending the approach toward the determination of the radial profiling of conductivity (and thus temperature) in cylindrical rods. Since the depth of electromagnetic penetration in a conductor is frequency-dependent (the skin depth effect), the analysis of impedance measurements over a wide frequency range can



potentially determine the conductivity as a function of depth. In addition, such methods show promise for following the decomposition of supersaturated solid solutions during HIPping because this will be reflected in a change of long-range electrical conductivity.

### Acoustic Emission Sensors

Even though the physical understanding of acoustic emission (AE) phenomena is less than complete, there are nevertheless important practical examples of the application of AE to a wide variety of practical metal-processing procedures.

#### Spot Welding

Resistance spot welding consists of compressing two metal parts together and passing a current of sufficient magnitude to cause local melting to form a weld. It has been a successful joining method for many years but suffers from occasional cracking problems exacerbated because the spot weld is usually buried between two sheets, making inspection both difficult and costly. AE has proved to be a successful method for overcoming this problem (Jon et al., 1978a, 1978b; Vahaviolos et al., 1976, 1981).

Resistance spot welding consists of the following sequence: Electrodes are set down on a part, a force is applied, current flows causing melting and nugget formation, the current is removed, cooling occurs, and the electrodes are lifted off. It has been found that each component of the process generates detectable acoustic emissions, as shown in Figure 5-17.

The signals from individual components of the process, such as set-down, initiation of current, and nugget formation, are related to electrode condition, surface condition, nugget volume, etc., and provide a basis for closed-loop feedback control of process variables. Deleterious conditions such as metal expulsion and post-weld cracking also generate additional distinctive AE signals, allowing their detection and control. It is therefore apparent that AE techniques can be used for the optimization of this joining process and similar processes (Saifi and Vahaviolos, 1976) to increase production and quality.

#### Electron Beam Welding

Electron beam welding has a low heat input that results in a finer grain size, a smaller heat-affected zone, and less distortion compared with some other welding processes. It is thus becoming an increasingly used welding method in situations where high-quality welds are essential. One area is the welding of superalloys. Here, however, grain boundary cracking is known to occur often at the weld root. The detection of this cracking has proved very difficult using conventional nondestructive methods such as dye penetrants, x-ray radiography, and ultrasonics.

Dickhaut and Eisenblatter (1975) explored the use of AE to detect the cracking as it occurs during the welding process. They made two principal

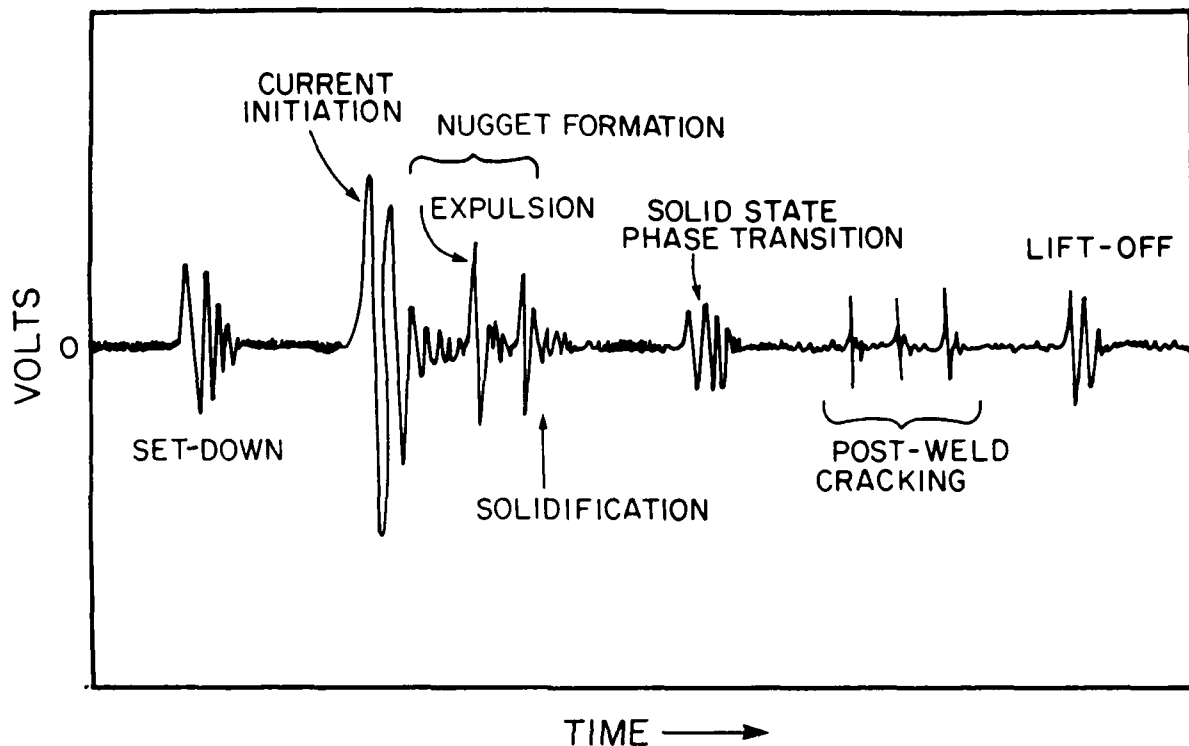


FIGURE 5-17 Acoustic emission signals typically detected during resistance spot welding. The signals from the normal sources of welding (such as set-down) and the detection of cracking allows closed-loop feedback control of the welding and on-line quality control.

observations. First, a continuous (background) AE activity was observed. The intensity of the signal varied with process variables such as energy input, feed rate, and focal spot size. Systematic investigations of the effect of these variables led to the conclusion that the origin of this acoustic emission was the motion of dislocations, probably in the very hot resolidified material. This was supported by tensile test data that showed that the alloys of interest generated much more intense acoustic emission at high temperatures, in accord with the studies of Hsu and Ono (1980).

The second observation was the discovery of discrete and individually energetic signals during the welding process. The generation of these was linked to the formation of intergranular cracks. The signal-to-noise ratio for these crack emissions was sufficiently high to lead Dickhaut and Eisenblatter to conclude that this cracking could be reliably detected.

However, the very sensitivity of the AE technique in this application is also a disadvantage. It results in the detection of cracks that are

normally considered as acceptable defects. Dickhaut and Eisenblatter attempted to find a correlation between AE amplitude and crack size. Because of a lack of control over the crack size and the distance between the source and the receiver, no correlation was determinable. The inability to size cracks turns out to be a critical shortcoming of the technique because it is uneconomical for welds with only small cracks.

The problem of defect sizing using acoustic emission is difficult because of the complicated transfer function of the parts in which crack growth occurs. Intensive research programs at a number of institutions are addressing the issue, but until it is resolved it will be difficult to exploit fully the potential for in-process weld monitoring.

### Heavy-Section Welding

The most common site of failure in large structures fabricated from heavy-section steels is in the vicinity of the weld. These failures are initiated by defects formed during welding that are often very difficult to detect with conventional nondestructive methods. When defects are detected, the repair of the thick sections can leave a weld with worse problems than that of the original flaw because of damage to the weld microstructure and additional residual stresses. The repair of these welds is a major cost item in the production of components manufactured from heavy-section steel.

The removal of flaws through in-process detection and repair would both improve repair quality and, provided that only one or two weld passes are removed and replaced, result in considerable cost savings over conventional heavy-section post-weld repair. The obstacle to this has been a lack of effective in-process sensors to detect flaws in situ as they form. In-process monitoring using acoustic emission shows promise for providing the much-needed tool (Bentley et al., 1982; Prine, 1980).

The primary problem is that, in contrast with electron beam welding, both flaw formation and the welding process itself generate acoustic emission. However, simple spatial and temporal filtering (cluster analysis) has been quite successful in discriminating defect signals from noise. As an example, Bentley and coworkers (1982) conducted a trial during which they monitored automatic and submerged arc welding of plates of a pressure vessel and stainless steel type 316 into which 20 defects were deliberately introduced. Two sets of instrumentation were used to monitor the welding, the primary difference being the positioning of the transducer pairs on opposite surfaces. Conventional nondestructive evaluation methods were used to establish that the intended defects were indeed produced; these methods also detected some unintended "natural" defects.

It was found that one or the other of the instrumentation sets detected 15 of the 20 defects introduced and that each alone detected 10. Cracks and slag inclusions were more readily detectable than other defect types (Table 5-3). Other studies have indicated that cracking during post-weld treatments can also be sensitively detected in reactor steels (Jax, 1973).

TABLE 5-3 Welding Defect Detection and Acoustic Emission

Plate Material	Welding Method	Intended Defect	Defect Type
Mild steel	Manual metal arc	Two hot cracks; slag inclusion; porosity; lack of fusion	Two cracks; slag inclu- sion; porosity; lack of fusion; lack of fusion and/or slag <sup>a</sup>
Mild steel	Automatic sub- merged arc	Hot crack; slag inclusion; two areas of porosity; lack of fusion	Crack; slag inclusion; one area of poro- sity; lack of fusion and/or slag; crack and/or slag
Stainless steel	Automatic sub- merged arc	Two hot cracks; slag inclusion; porosity; lack of fusion	Two cracks; lack of fusion and/or slag; lack of fusion and/or crack

<sup>a</sup>Natural (unintended) defect

Studies such as these clearly demonstrate the potential of in-process weld monitoring by acoustic emission. The remaining obstacles to the implementation are techniques (a) to separate defect signals from noise more reliably and (b) to characterize flaw severity for input into accept-reject criteria. Other supporting studies of the role of metallurgical and welding variables ought also to be carried out to determine the bounds of "quiet" flaw growth.

#### INVERSE PROBLEMS

The sensors that are emerging for materials process control are based on a wide variety of scientific laws. They almost all possess a common feature. That is, the electrical signal they produce can be expressed as a relationship between cause and effect.

Provided both the "law" and "cause" are known, it is relatively straightforward to predict effects. This is the so-called direct or forward problem described in the earlier section on Sensor-Media Interaction Models. However, for process-control purposes, one often needs to know "causes" from their detected or measured "effects." This is the so-called inverse problem. Unfortunately, the electrical signal (the effect) also usually contains random noise that introduces error into the deduced cause. For many of the more complex sensors, the solution of the inverse problem not only is nontrivial but also may introduce subtle

errors and ambiguities due to numerical instabilities that may completely invalidate the solutions. For example, for some phenomena, the inverse law may be infinite or nonunique over some domain of interest.

If sensors are to be fully exploited, it is essential that the limitations of inverse (signal analysis) methods be recognized from the outset and sensor designs be evolved to mitigate this problem.

#### SUMMARY AND FUTURE NEEDS

The emergence of advanced sensors coupled with process modeling and artificial intelligence and expert systems has created the possibility of new approaches to materials processing. Each of the processes controlled is more amenable to full implementation of computer-integrated manufacturing, where process, quality and product control, and flexible manufacturing technologies may be merged into a single, plant-wide, flexible manufacturing system with enhanced productivity and product consistency and substantially reduced costs.

The sensor needs for materials processing are very demanding of today's measurement science. They are, however, intimately linked to the level of process understanding. Generally, the better the process is understood and capable of predictive modeling, the less stringent are the needs for sensors. Conversely, the more fully a process is characterized by sensors, the less the dependence on process models for process control. In devising the control strategies for new processes it is important to assess the availability both of process models and of sensors.

For materials processing, a premium is placed on those sensor methodologies capable of noninvasively probing the interior of generally high-temperature opaque bodies surrounded by an aggressive environment. Ultrasound, eddy currents, and new laser techniques are finding particularly innovative applications for this because of their remote-sensing capability. The laser generation of ultrasound when coupled with EMAT receivers can form the basis for a noncontact sensor. This approach promises the emergence of ultrasonic sensors for determining the microstructure, including grain size, texture, inclusions, defects, interfaces, residual stresses, surface modification, and internal temperature. Similar opportunities exist for eddy current sensors.

It is evident that, even though there are no major technological roadblocks to the development of numerous metals processing sensors (and indeed none may have existed for the past 5 years), the pace of sensor development has been slow, and at present it limits the implementation of many process control scenarios. One reason for this may be the "application-specific" nature of many sensors. Potential markets for sensors are often small, whereas the cost and risk for their development is great. Collaborative programs in the metals industry such as those sponsored by AISI and the Aluminum Association share the cost and risk and may be one mechanism that can encourage sensor development. More extensive government funding of generic measurement sciences is also urgently needed, given the impact a generation of sensors could have on the international competitiveness of the domestic metals industry.

## REFERENCES

- Alers, G. A., and H. N. G. Wadley. 1987. Progress in Quantitative Nondestructive Evaluation, Vol. 6. D. O. Thompson and D. Chimenti, eds. New York: Plenum Press.
- Bentley, P. G., D. G. Dawson, and D. Prine. 1982. Report ND-R-767(R). Risley Nuclear Power Development Establishment.
- Birnbaum, G., and G. S. White. 1984. Research Techniques in Nondestructive Testing, Vol. VII. R. S. Sharpe, ed. New York: Academic Press.
- Dickhaut, E., and J. Eisenblatter. 1975. J. Eng. Power, 97:47.
- Elkind, B., M. Rosen, and H. N. G. Wadley. Met. Trans. A, in press.
- Horvath, V. V. 1985. NDE of Microstructure for Process Control, p. 47. H. N. G. Wadley, ed. Metals Park, Ohio: American Society for Metals.
- Hsu, S. Y. S., and K. Ono. 1980. 5th Int. Acoustic Emission Symposium. Tokyo, Japan.
- Jax, P. 1973. Proceedings of the 2nd Int. Conf. on Structural Mechanisms in Reactor Technology (Berlin). Nucl. Eng. Des. 27(1):73.
- Jon, M. C., H. A. Duncan, and S. J. Vahaviolos. 1978a. Mater Eval. 36(11):40.
- Jon, M. C., C. A. Keskimaki, and S. J. Vahaviolos. 1978b. Mater. Eval. 36(4):41.
- Kahn, A. H., and H. N. G. Wadley. 1986. Proceedings of Aluminum Association Temperature Measurement Workshop, Atlanta, Georgia. Washington, D.C.: Aluminum Association.
- Kear, B. H., E. M. Breinan, and L. E. Greenwald. 1979. Metals Technology, p. 121 (April).
- Kittel, C. 1971. Introduction to Solid State Physics, 4th edition. New York: John Wiley and Sons.
- Kossowsky, R. 1983. Designing an analytical microscopy laboratory. 35(3):47-53.
- Libby, H. L. 1971. Introduction to Electromagnetic Nondestructive Test Methods, Ch. 5, pp. 135-150. New York: John Wiley and Sons, Inc.
- Lion, K. S. 1969. Transducers: problems and prospects. IEEE Transactions on Industrial Electronics and Control Instrumentation, IECI-16, No. 1 (July).
- Mansfield, T. L., and C. L. Bradshaw. 1985. NDE of Microstructure for Process Control, p. 190. H. N. G. Wadley, ed. Metals Park, Ohio: American Society for Metals.

- Mehrabian, R. B., and H. N. G. Wadley. 1985. *Journal of Metals*, p. 5 (February).
- Mehrabian, R. B., R. L. Whiteley, E. C. van Reuth, and H. N. G. Wadley, eds. 1982. *Process Control Sensors for the Steel Industry*, report NBSIR 82-2618. Washington, D.C.: U.S. Department of Commerce.
- Middelhoek, S., and D. J. W. Noorlag. 1981/82. Three-dimensional representation of input and output transducers. *Sensors and Actuators*, 2:29-41.
- Morris, C. J., and D. M. Keener. 1986. *Proceedings of the Second National Seminar on NDE of Ferromagnetic Materials*. Houston, Texas:
- National Materials Advisory Board. 1986. *Automated Nondestructive Characterization and Evaluation in Metal and Ceramic Powder Production*. Report Numbers NMAB-442 and MTL TR 86-34 (Limited Distribution). Watertown, Massachusetts: Army Materials Technology Laboratory.
- Nassau, K. 1983. *The Physics and Chemistry of Color: The Fifteen Causes of Color*. New York: John Wiley and Sons.
- Prine, D. W. 1980. 5th Int. Acoustic Emission Symposium. Tokyo, Japan.
- Saifi, M. A., and S. J. Vahaviolos. 1976. *IEEE J. Quantum Electron.* 12(2):129.
- Vahaviolos, S. J., M. F. Carlos, S. J. Slykhouje, and S. J. Ternowchek. 1981. *Mater. Eval.* 39:1057.
- Vahaviolos, S. J., V. C. Paek, and G. E. Kleinedler. 1976. *IEEE Trans. Ind. Electron. Control Instrum.* 23(2):123.
- Wadley, H. N. G., S. Norton, F. A. Mauer, and B. E. Droney. *Proc. Royal Society of London*, 1986, in press.
- Wayne-Norton, L., W. Hill, and R. Brook, Jr.. 1977. *J. NDT* 17:242-248.

## Chapter 6

### IMPLEMENTATION OF ON-LINE PROCESS CONTROL

The implementation of on-line process control (OLPC) is the final and most difficult step toward true process automation. The necessary background and individual system(s) integration needs for OLPC have been previously discussed. Proper sensor location, control systems durability, data bases, and accessibility as previously cited are mandatory to success.

Prior to the design and construction of an OLPC system, accurate definition of the business objective is first required. The primary goal of most materials processing facilities is directed toward "built-in" rather than "inspect in" product quality and reliability. This generic objective often constitutes the intended product cost superiority needed to justify capitalization of OLPC ventures. Other goals are important to implementation success, but the cost goal is fundamental to the success of any OLPC venture.

When building in quality, the necessary systems requirements for finishing processes, as opposed to primary processes, are rather easily determined. For example, for finished machining, adherence to dimensional tolerances is an easily defined "data base." (Although the OLPC for satisfying this objective is less easily defined, the fact remains that the product goal is definable through drawing and specification requirements.) Conversely, building in quality in a complex (or even simple), high-integrity investment casting, for example, is a much more difficult undertaking. Fortunately, much DOD and industry study has gone into "foundry of the future" concepts formulating the basis for future needs. The remainder of this chapter is, therefore, for clarity and example only, referenced principally to investment casting, with parallel examples cited where applicable to other real and potential OLPC ventures.

#### TRADITIONAL APPROACH

For purposes of discussion and to present the needs of implementation of on-line process control, manufacturing of aircraft engine components is considered here. A major emphasis within the aircraft engine industry is to achieve cost-effectiveness for its products by replacing today's fabricated or forged machined structural engine components, such as frames, casings, and engine mounts, with one-piece near-net-shape structural



castings. A second major commitment is to further expand the use of cost-effective methods for producing complex turbine airfoil castings. This philosophy has affected and will affect the cost of gas turbine engines significantly by reducing development time, part inventory, and manufacturing cycle time.

Aircraft engine manufacturers have aggressive programs in which castings are becoming increasingly more complex. The capacity of the foundry industry is clearly forecast to be limited as a result of the expected increasing business volume and the ever-more stringent demands for casting integrity.

The primary reason for the limitation is not the lack of the art and skills needed to produce the high-quality complex castings required by the engine industry; what is lacking is the fundamental understanding of unit processes and adequate process control. Computer technology and advanced sensors are key tools for overcoming the bottlenecks of the foundry industry, which traditionally has depended on individual craftsmanship.

The use of traditional foundry engineering techniques to develop manufacturing processes has not always yielded optimum processes. This is because these traditional techniques have been based largely on empirical methods, intuitive experimentation, and keen observation of the response of the solidifying casting to variations in process variables. It is generally not possible to predict the course of solidification of a given casting; as a consequence, much time is spent in attempting to find a process that can economically produce the casting, even if it is not optimum. The result is that additional casting costs are incurred, and casting quality, although meeting the demanding specifications, has not achieved its ultimate level. In brief, the level of process engineering and operator skill, rather than OLPC, dictates the profitability of foundries. Absence of OLPC will be shown to be related to sensors, data bases, and specific equipment capability (i.e., the tools needed for OLPC do not yet exist).

Procedures taken to establish a production process for a new part are shown in Figure 6-1. Because of the complexity of the geometry and the necessary tooling (wax dies, core dies, fixtures, and gauges), it may take up to 8 months to design and procure a new part. Once the tooling is received and the "best-guess" process defined, casting trials will proceed. Each casting trial and evaluation can take up to 2½ months. This trial-and-error procedure continues until a production process is established. Unfortunately, time constraints on these critical engine components usually require the foundry to establish a production process before there is the opportunity to optimize all processing variables. This can lead to a more costly procedure that, while acceptable for product application, does not provide the highest achievable quality or yield. In some instances, component design concessions must be taken to establish a process in the required time frame. At that point the process is established, and the product of the process is fully evaluated, which documents the casting's metallurgical and dimensional integrity. This expensive and exhaustive evaluation is necessary to ensure that all quality requirements have been fulfilled for the production process identified. It is not uncommon for a new complex investment casting to

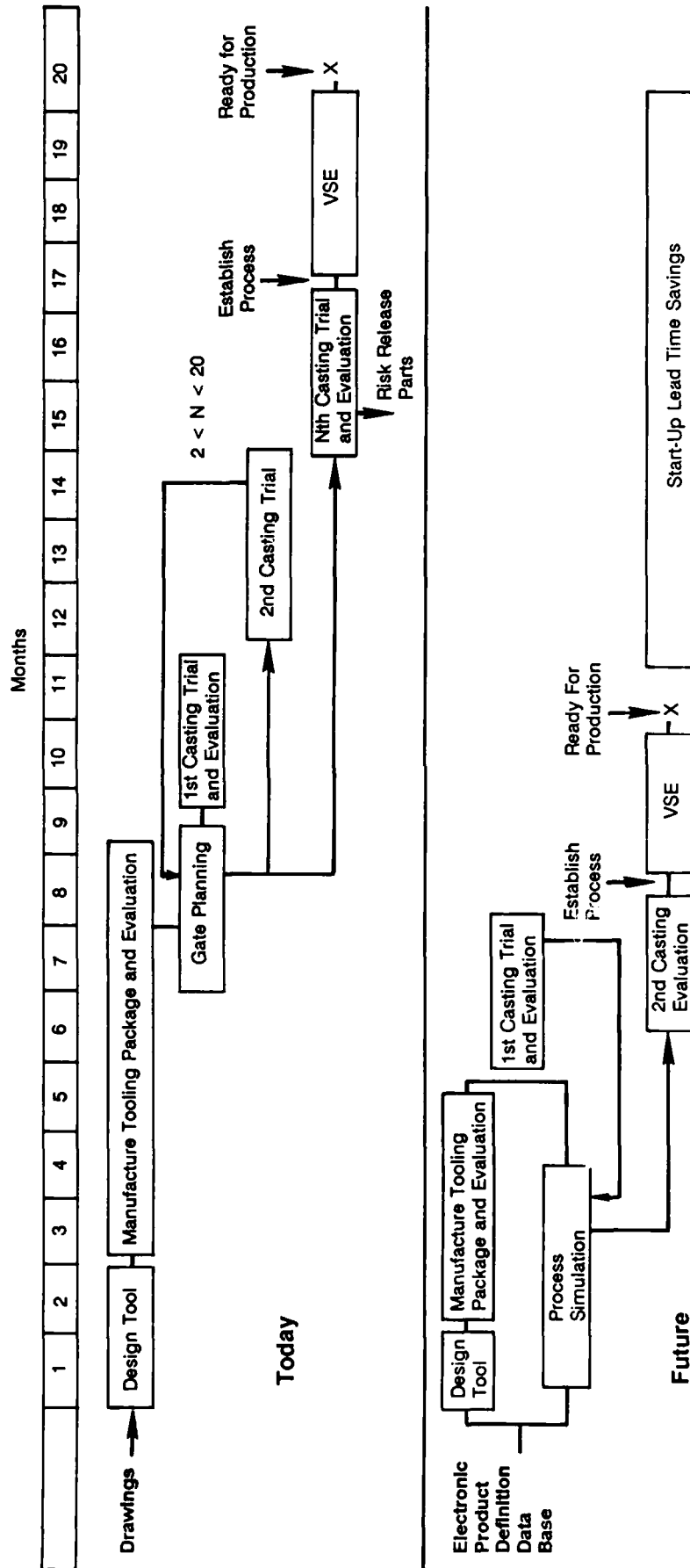


FIGURE 6-1 New part start-up schedule.

take up to 2 years from the time the development order is placed until the production process is established. From this point on, any modification in the established process must be subsequently evaluated to determine its influence on casting integrity. This entails additional expense and time; therefore, it is desirable to establish the production process with as much investigation of the influence of the processing variables as possible to achieve the best process, and with as much tolerance to processing variables as possible. This initial product iterative process, which is also necessary for process changes, is the direct result of lack of process understanding and the data bases needed to interrelate casting process variables.

#### FUTURE CASTING PROCESS

In the foundry environment, barriers to casting quality, lead time, and cost of new development parts must be addressed to fulfill the needs and objectives of the business. New approaches are essential if the foundry industry is to meet challenges provided by the product users. The use of computer-aided design (CAD), computer-aided engineering (CAE), and computer-aided manufacturing (CAM), coupled with artificial intelligence (AI) and, particularly, expert system (ES) techniques, offers a technological means to aid current and potential casting suppliers in resolving technical barriers to reducing the development cycle for new investment castings.

Aggressive programs are in place to incrementally implement and train key investment casting vendors in the use of these new technology tools in a logical fashion. This starts with the fundamentals of electronic data transfer, moves on to CAD, and proceeds to more sophisticated CAE capabilities to predict the course of solidification. Next, CAM techniques will be used to improve tooling procurement. In-depth studies are being made that will apply these new tools to achieve the largest benefit and further define the benefits achievable by expert systems. The necessary tools are being generated for access by the computer-aided environment along with integration of all tools to assist the investment casting vendors in the routine aspects of problem-solving. This incremental implementation plan will allow foundries to recognize an immediate payoff (Figure 6-2) while learning the capabilities and building proficiency in their operation.

The overall strategy is to direct a well-integrated technology initiative toward anticipated advancement in foundry and computer technology. DOD activities, such as the Army's Solidification Simulation and the Air Force's TechMod and ManTech programs, along with rapid advancements in computer technology, such as parallel processing and intelligent software integration, provide emerging opportunities for modernization of a foundry. This concerted effort will enable the foundry engineer to gain a better understanding of the unit processes by evaluating many of the cross-linking variables in a computer-aided environment prior to producing a casting. Also, the tooling procurement cycle and precision will be enhanced by improved electronic definition of the casting geometry and by utilizing computer-aided capability to effectively design and manufacture the wax dies, core dies, fixtures, and gauges. As shown in Figure 6-3, with these capabilities in place, it is anticipated that a production

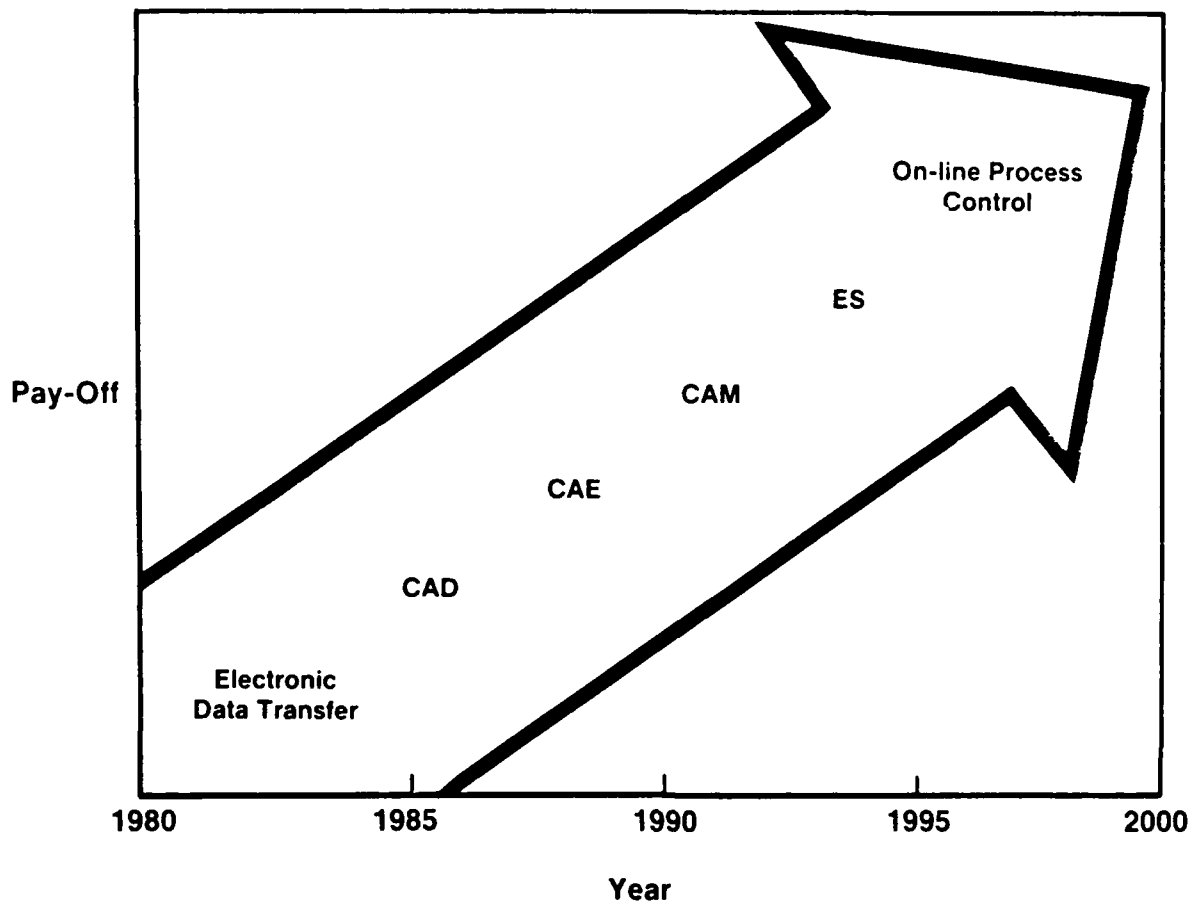


FIGURE 6-2 Incremental implementation of computer-aided technology.

process would be established on a new part in half the time it takes today. The long-term goal is to implement a computer-integrated castings (CIC) capability in the U.S. investment casting industry. This will increase the effectiveness of casting design, development, and manufacturing through the introduction of new tools involving CAE, CAD, CAM, ES, and OLPC technology, as shown in Figure 6-3. The CIC concept relies on a well-integrated investment foundry to readily accept state-of-the-art electronic product definition from various aircraft engine manufacturers. This information would become the heart of the CAD, CAE, CAM, ES, and OLPC functions to be performed at all levels of design, engineering, and manufacturing. There are various expert systems that could aid and prompt the foundrymen through the various tasks to be undertaken. For example, ES could be applied to the selection of critical, cross-linking parameters (gates, risers, metal superheat, mold preheat, etc.). ES represents the key technology for capturing the years of valuable casting experience available.

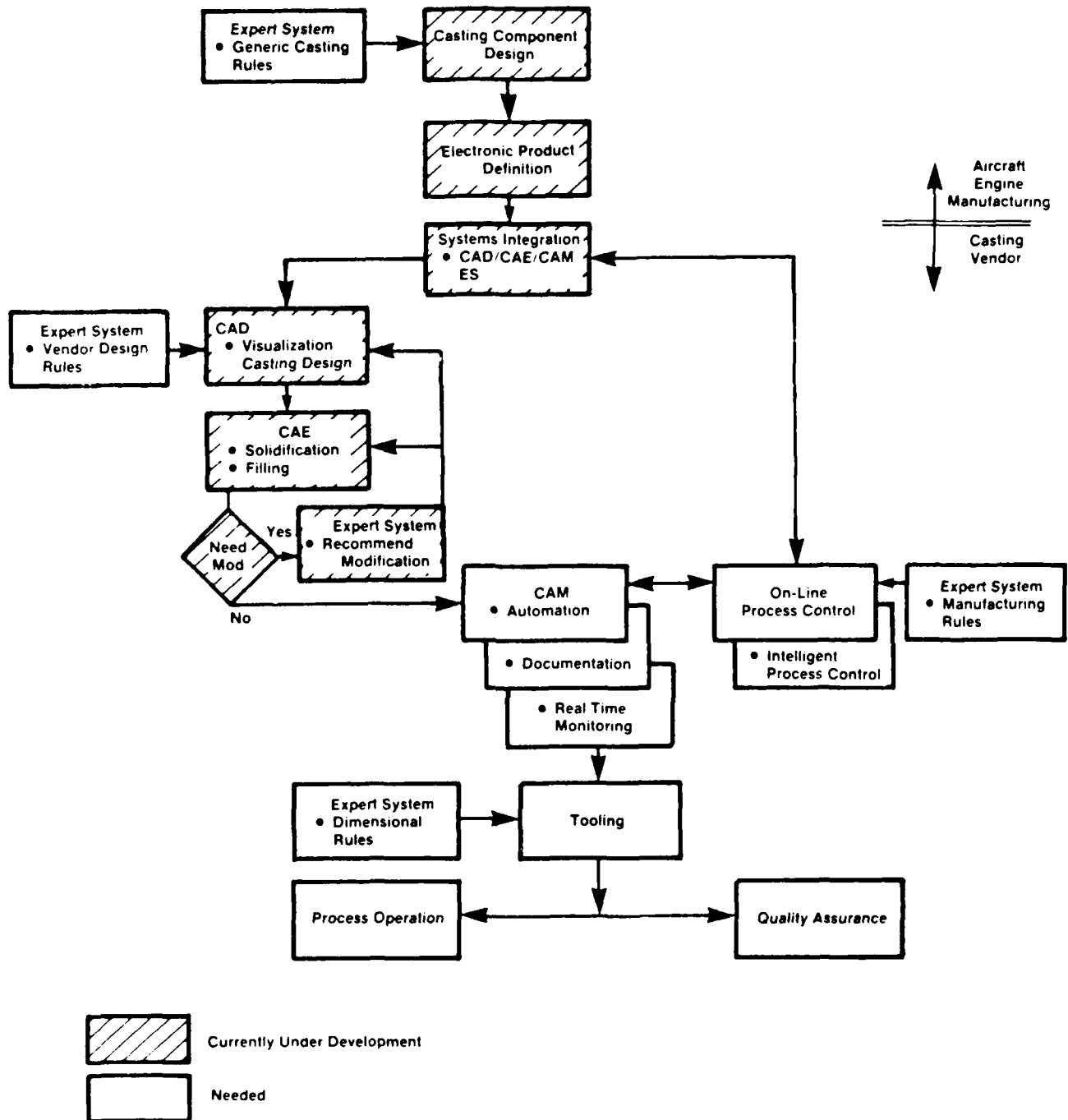


FIGURE 6-3 Computer-integrated casting.

## PROCESS CONTROLS IN FORGING

Forging OLPC has been implemented to a much higher state than casting and is included here to demonstrate that OLPC for primary metal processing can be successfully implemented.

Traditional forging techniques are largely based on empirical methods, intuitive experimentation, and observation of the response of the forging process to variations in process variables. As with casting (and other processes), much time is spent on finding a process that works, but this is generally not the optimum. The result is that, although demanding specifications are met, quality and cost are unbalanced relative to attaining the highest quality at minimal cost.

Forge processing windows for advanced aerospace materials are narrow, making control of equipment difficult. Therefore, effective press control uses computer-based technology. In order to control a process, one must completely understand the process dynamics. Modeling of the system provides the key to that understanding. The closed-loop forging process diagram (Figure 6-4) is a conceptual idea on how different technologies can be linked to provide overall process control.

The finite element process model ALPID provides information on metal flow, forming load, stress, strain, strain rate, and temperature distributions in the workpiece during forging. Working from the ALPID-generated forging loads, die stresses and deflections can be evaluated.

Dynamic material modeling methodology characterizes the intrinsic workability of the workpiece material to permit identification of optimal processing conditions (processing windows) in terms of deformation rate and temperature without resorting to costly iterative experiments. Under these specific conditions, materials can be fabricated to obtain a desirable microstructure.

Together with ALPID, the dynamic material map yields a control algorithm for ensuring forging quality and performance on a repeatable basis--i.e., microstructure, mechanical property, and tolerance control (Figure 6-5). Material behavior models aid in estimating equipment requirements and controlling the microstructure in the product. Process simulation models predict the material flow during the deformation process. The process control system uses this information to control the process variables of deformation rate and temperature so that they lie within specific regions to achieve the required microstructures and properties within the product. Thus, via process simulation, controls can be built into the process that lead to improved quality, less inspection, and better testing procedures by identifying critical regions in the product.

On-line real-time process and equipment control is required to achieve this more favorable condition. Forging OLPC involves the following steps:

- Design the manufacturing (forging) process
- Simulate the process using analytical modeling techniques
- Perform sensitivity analysis

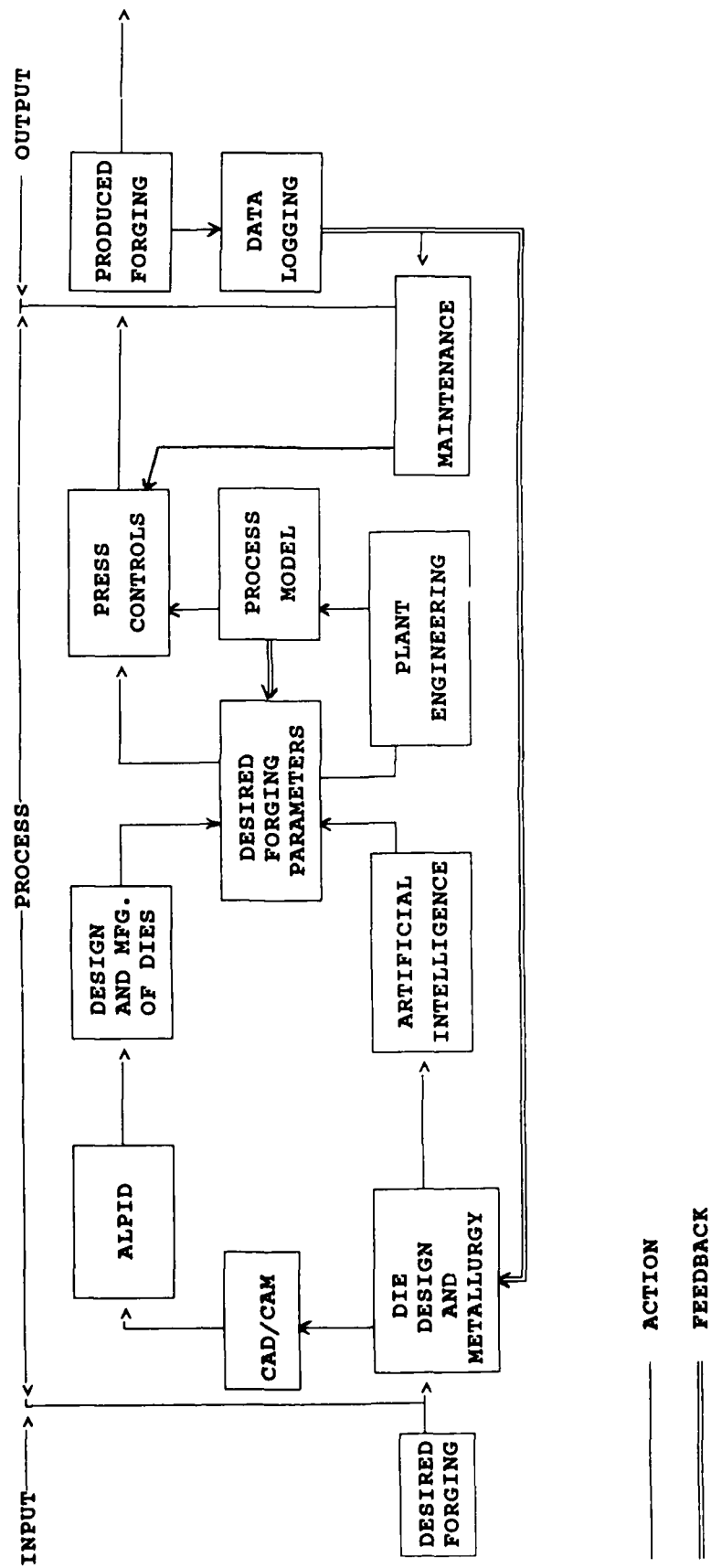


FIGURE 6-4 Closed-loop forging process.

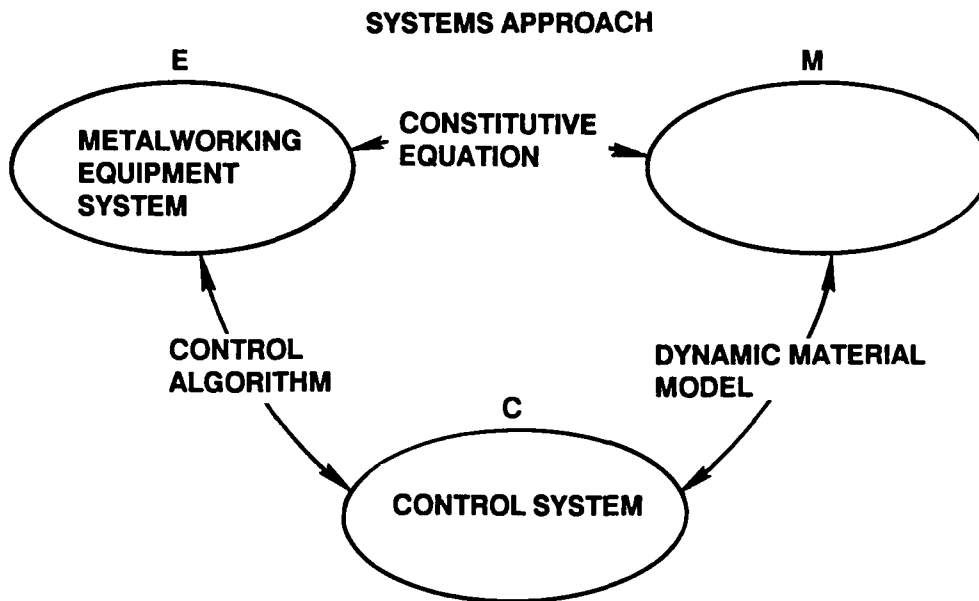


FIGURE 6-5 Schematic representation of metal-processing system from physical-systems-modeling viewpoint.

- Determine variables and items to be controlled and with what limits
- Decide on sensors and type
- Devise control algorithms based on process simulation and sensitivity analysis
- Provide feedback for control of process and equipment and their real-time adjustments

The controllable factors in forging are the following:

- Number of forging steps and preform shapes to achieve the desired amount of incremental metal flow
- Workpiece temperature and effective strain rate (e.g., forging press speed)
- Ratio of mean stress to effective stress (normally less than 2/3 to avoid tensile stresses and hence the possibility of crack formation)
- Die temperature, deflections, and alignment
- Furnace temperature, heating rate, and time at temperature for the workpiece
- Transfer time from furnace to press
- Coatings and lubricants
- Billet shape, quality, and cleanliness

Problems and defects encountered when process control is inadequate are nonhomogeneous flow, surface and/or internal cracking, hot shortness, die chilling, lubrication breakdown, grain growth, and die cracking.



The majority of sensors needed in forge process controls are relatively inexpensive. The key, as with other processes, is to understand where these need to be used and the selection of the controlling process parameters, which will ensure the required part quality along with specific mechanical and physical characteristics. Sensors are required for controlling and monitoring of time, pressure, temperature (contact or noncontact type), die or press velocity, die deflection, and dimensions.

As the concept of intelligent processing of materials (IPM) achieves maturity, more sophisticated, costly sensors will be required. Under the IPM approach and strategy, optimal process control is acquired only by monitoring or sensing the fundamental microstructural and metallurgical characteristics governing the product quality. For example, if a particular disk forging requires a grain size limit, optimal IPM control advocates use of a sensor (e.g., ultrasonic-based) that can discern grain size and other microstructural features. Advanced sensors for the forging industry will require considerable development.

On-line sensors provide the necessary information for real-time feedback control to keep the process within the processing window. As on-line sensors are implemented, in combination with process models to determine the best monitoring parameters and location, the need for post-manufacturing inspection decreases. Not only can the on-line information be implemented in "intelligent" material processing, but also the information can be used to identify location of potential defects. This could be detected directly by the sensor or predicted by the process models using sensor information. The implication is that only selective post-inspection at specific locations will be necessary, thereby significantly reducing inspection cost.

Process simulation and control was first demonstrated by the Air Force for the isothermal closed-die forging of a dual property Ti-6242 disk, where the strain rate at critical regions of the workpiece was controlled to be within the stable processing region (Malas, 1986). Many additional demonstration and limited production incorporations of forging OLPC have since been completed. Further product applications are in progress, and state-of-the-art availability of this technology is available for generic application.

#### PARTICULATE PROCESSES

The need for OLPC of particulate processes such as metal powder atomization and ceramic powder manufacture has been established in a prior NMAB study (National Materials Advisory Board, 1986). Although progress toward OLPC of metal powder atomization has been made, product demonstration has yet to be realized.

There has, however, been progress in the refining of bauxite. Alcoa has been developing an advanced control strategy for one of the critical steps in the bauxite refining process, which produces alumina, the feedstock for smelting aluminum. Figure 6-6 shows the basic steps in bauxite refining, otherwise known as the Bayer process. Crushed bauxite is mixed with a recycled caustic soda solution and then digested at elevated tem-

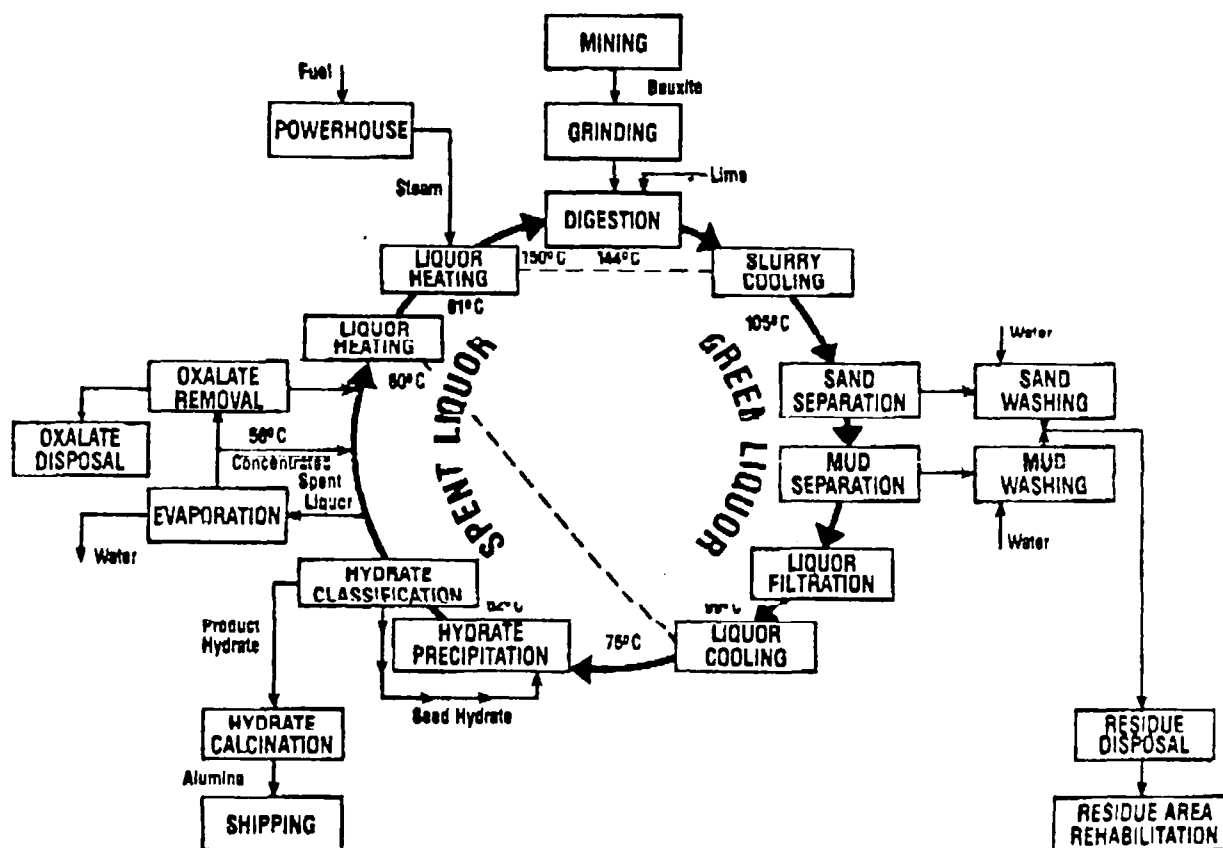


FIGURE 6-6 A commercial alumina refinery flow diagram.

perature and pressure. This step dissolves the alumina hydrate while most of the impurities from the bauxite remain as solids. These solids are then removed in a sequence of solids-settling operations. The resultant clear liquor is regeneratively cooled to produce a supersaturated solution of sodium aluminate.

Obtaining suitable product quality and particle size distribution in the precipitation section is crucial. Process control at several levels has been implemented or is being developed to ensure acceptable product consistency with regard to impurities and size, improved yields, and reduced manpower levels.

The precipitation area control scheme has been designed with a hierarchical structure. The lower-level controllers are designed to function even in the absence of the higher-level controls, while the higher-level controllers rely on the lower levels to implement their specified control actions.

The lowest level of control consists of certain field instruments and regulatory controllers coordinated by a distributed digital system with a centralized control station. The next higher level calculates setpoints for flow or temperature controllers in accordance with algorithms that

reside on the area process computer. This computer also stores historical process data for trend displays. It will also house the advanced control algorithms, which will control the precipitation conditions in the seeded precipitator tanks to give the desired product quality.

The advanced control algorithm handles a multivariable control problem to control growth rate and particle size distribution in the precipitation tanks by manipulating the seed slurry recycle rate and makeup. It has been designed to minimize interaction among the control loops and was tested on a comprehensive dynamic model of the precipitation system. The dynamic model represents the thermodynamic properties of all important components as well as the kinetics of all the mechanisms resulting in particle growth.

The control algorithm design is complicated by the fact that some measurements, such as liquor composition and particle size distributions, are available only at relatively long time intervals. Substantial work on both the durability and sampling apparatus of proposed sensors is required to get on-line measurement. For now, the liquor composition is analyzed in a lab and a slurry sample must be carried to a particle size analyzer. Since some of these analyses may be done only every few hours, a discrete controller was designed to accommodate the sampled-data-system nature of the problem.

The advanced control algorithm has demonstrated the ability to handle such disturbances as changes in inlet liquor rate or recycled solids concentration with acceptable performance criteria.

The final levels in the control hierarchy consist of precipitation-area and plant-wide optimization. The optimization models have been developed from rigorous steady-state models.

Implementation of the entire hierarchical control system for the precipitation area is expected to improve the reliability of producing high-quality alumina at high yields.

#### FURTHER NEEDS

As previously stated, there is a concerted effort under way to develop and implement the necessary technology to address the needs for new casting process development--that is, electronic product definition and transfer, computer system integration, CAD, CAE, and some CAM (tooling) and ES (diagnostics). These technical areas are highlighted in Figure 6-3. This undoubtedly will have a major impact in the investment casting industry and is an excellent start in establishing CIC. Once the "normal" production process has been recommended with these new tools, the relationship between fixed casting parameters (i.e., alloy composition, gating system, etc.) and controllable casting parameters (i.e., metal pour temperature, ceramic mold preheat temperature, etc.), with resulting yields and microstructures as shown in Figure 6-7, will be better understood. Unfortunately, random manufacturing variations in these fixed and controllable casting parameters, along with variations in uncontrollable casting parameters (i.e., ceramic shell thickness variations, vacuum

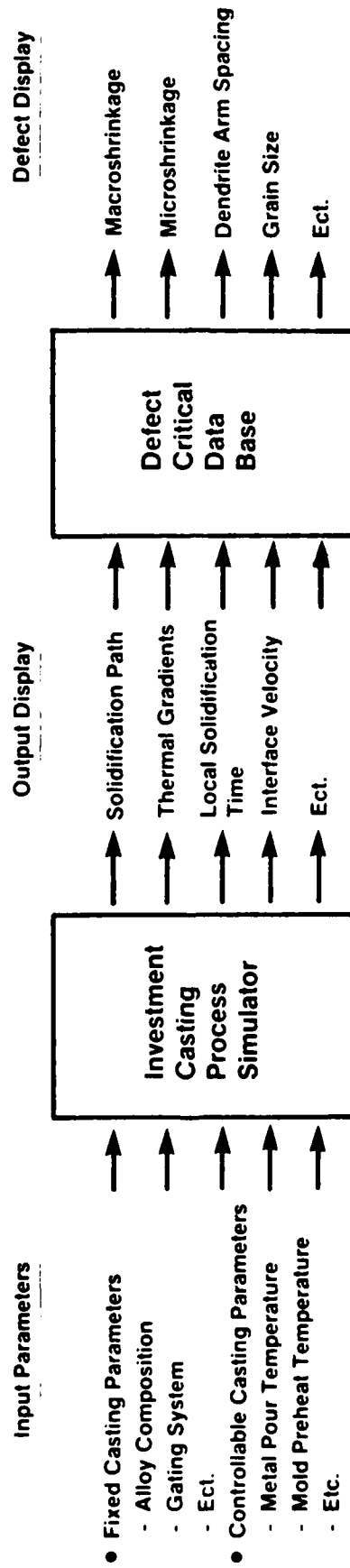


FIGURE 6-7 Information flow.

levels, ambient conditions, etc.), lead to casting inconsistencies. Adequate process control is often lacking. Because of random casting parameter variations, investment castings often lack reproducibility; this in turn requires that castings be overdesigned. Poor reproducibility thereby causes a substantial loss of the full potential of investment castings. In addition, current production investment casting is labor-intensive and requires costly post-processing inspections. Defects occur often and are typically not identified until late in the manufacturing process, thereby resulting in scrapping or intensive reworking. These post-processing operations result in extensive inspections; this prolongs the manufacturing cycle and increases costs.

The incorporation of expert system technology into the production operation can greatly improve casting quality and yield. Uncontrollable casting parameters such as shell thickness are fixed and unchangeable at the time of metal pour, but an ES-based control system can adjust the controllable casting parameters to compensate for variations among the "fixed" parameters. For compensation to be successful, the "fixed" parameters must be accurately measured using process sensors, and models must be available to allow the expert system to (a) determine the impact of the "fixed" parameter variations and (b) establish a process plan that restores the operation to normalcy. Although the implementation of ES control technology is in its infancy, due partially to "real-time" concerns, the strategy described can be carried out in advance of casting pour since only planning functions are performed.

As the state of the art advances for ES control technology, the entire casting operation will be subject to ES implementation--for both controllable and fixed parameters. Under this scenario, the ES controller will chart a process trajectory for the key parameters of the casting operation. As processing ensues, the controller will continually determine the process state (from sensor data) and identify whether the process goal will be attained (from process models). As with the earlier example, an ES-based controller is recommended because of its ability to handle both quantitative and symbolic knowledge representations and the wealth of solution paradigms available using AI-inspired computer language.

For OLPC to be successful in enhancing the capabilities of process automation, various technical and economic barriers must be considered. These barriers include sensors, data bases, factory hierarchies, system flexibility, system integration, and implementation cost. Examples of each are stated as they pertain to investment casting and in particular directional solidification investment casting, both multigrain and single crystal (SC). These investment casting processes are used extensively in producing complex airfoil configurations for aircraft engine turbine blades and vanes.

The specific example of directional solidification (DS) can be used to illustrate other pertinent OLPC considerations. First, DS processing by its nature demands process control to achieve product objectives. Second, and perhaps most significant, directional solidification requires near steady-state process control. This need simplifies OLPC objectives in that sensors, feedback, and controls technology are more readily adapted to a steady-state mode. A nearly opposite case is that of pouring molten metal into a ceramic mold to produce equiaxed castings. In this

case, local filling, thermal gradient, and solidification rates vary with a series of variables, some of which are little understood or characterized. The analogy points out the need to consider basic process changes as well as sensor and related process control technology in design of OLPC facilities (i.e., difficult-to-generate data bases and control schemes may be obviated via process changes).

### Sensors

Currently, process control of the investment casting process is limited to extrinsic parameters such as temperature and pressure. Intrinsic properties of the materials and other key parameters are usually not monitored during the process, preventing closed-loop feedback control. This appears to be a major flaw in current processing methodology.

Sensors are only used after production in an attempt to "inspect in" quality. What is needed is "built-in" quality through automated "intelligent" materials processing utilizing a system consisting of a process control model, on-line sensors, feedback controls, and artificial intelligence or expert systems. Although great strides are being made in process modeling, the measurement methods (sensors) and their associated analysis techniques (control schemes) definitely lag behind and are a major obstacle to the implementation of a total OLPC within CIC.

Sensors characterizing microstructure and measuring critical process variables during solidification are needed. Few exist today, but the need for sensors to characterize casting features such as grain size, microporosity, macroporosity, segregation, nonmetallic inclusions, and grain defects, together with process variables such as metal flow rate, heat flow, mold filling, metal or ceramic reactivity, and liquid-solid interface, has been identified.

Sensors are still viewed as a weak link in "intelligent" solidification processing. A complicating issue with development of these sensors is the lack of basic knowledge of the relationship between sensing mechanisms and microstructure. Furthermore, the hostile environment in which sensors are needed (high temperatures and aggressive atmosphere), the limited time available for on-line process control, limited accessibility, and the need to avoid interference with the process itself all introduce constraints on practical sensor systems.

DS and SC investment casting processes involve solidification rates that allow sufficient time for on-line process control to influence the microstructural integrity. This is in contrast to other investment casting processes such as equiaxed airfoil and structural castings, which solidify rapidly, leaving inadequate time for feedback control. The key in situ sensor measurements needed to monitor the specific example of DS and SC process is the liquid-solid (LS) interface position and shape along with the thermal gradient ( $G$ ) at the liquid-solid interface. The solidification rate ( $R$ ) can be easily derived from the LS interface position and withdrawal rate. The propensity for many of the defects found in DS and SC castings (equiaxed grains, freckles, low-angle grain boundaries, etc.) can be expressed by considering both  $R$  and  $G$  parameters. Control schemes can be derived to monitor LS and  $G$  and regulate controllable casting parameters such as withdrawal rate, thus enhancing the casting integrity.

There are a number of sensor techniques, such as ultrasonic, eddy current, x-ray, laser, infrared, acoustic emission. Unfortunately, little has been accomplished to eliminate or narrow the domain of appropriate sensor schemes, and therefore the possibilities remain numerous.

As on-line sensors are implemented, in combination with process models to determine the best monitoring parameters and location, the need for post-processing evaluation will start to decrease. Not only can the on-line information be implemented in "intelligent" material processing, but also the information can be used to identify locations of potential deviate casting integrity. This could be detected by the sensor or predicted by the process models using sensor information as boundary information. The implication is that only selective post-inspection at specific locations for deviate casting integrity will be needed, thus eliminating the costly 100 percent inspection.

A successfully applied example of a process requiring sophisticated sensor technology is that of on-line machine tool monitoring. Implementation of this technology requires similar planning and ongoing systems evaluation, as with any other OLPC system. Although the level of effort required to develop the software and control systems should not be minimized, the key enabling technology for this system, shown schematically in Figure 6-8, was sensor development. This particular sensor features a "touch" mode for in-process measurement of part and tool dimensions and a break mode for the detection of unexpected tool breaks.

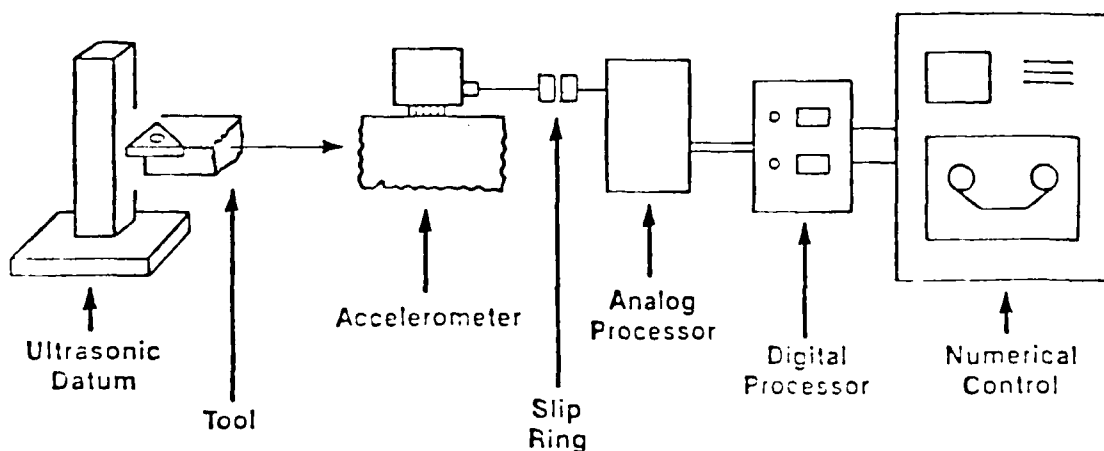


FIGURE 6-8 Machine tool monitoring system.

A tool-break sensor represented the most difficult challenge. The sensor development first required identification and isolation of cutting noise level. The basic monitoring technique is shown schematically in Figure 6-9. It was also necessary to determine the normal cutting signal artifacts such as those shown in Figure 6-10. The determination of the normal steady-state and transient conditions defines the total allowable operating range over which the machine tool must function for suitable factor performance.

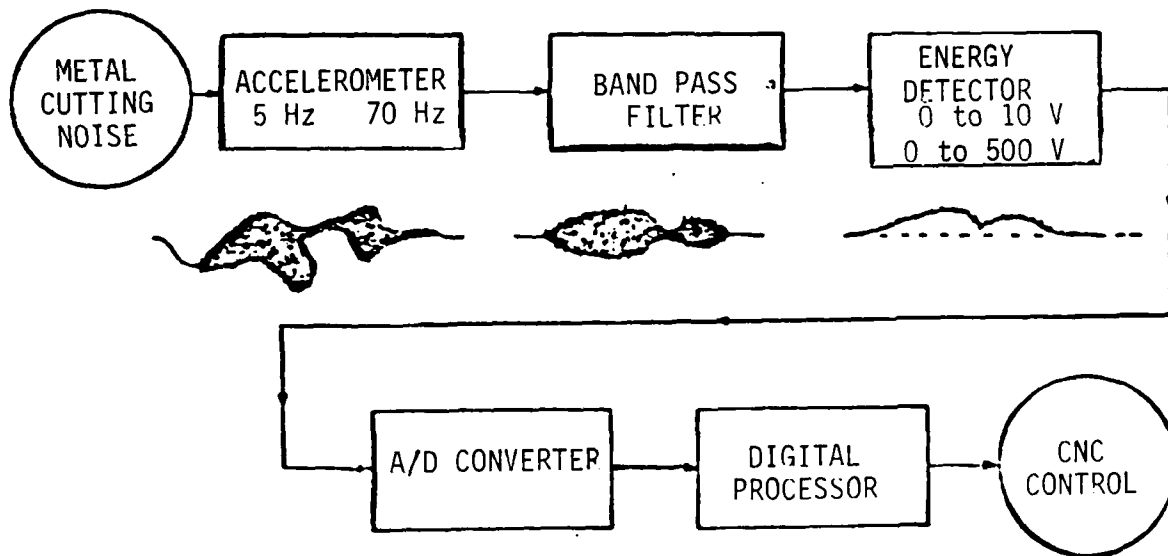


FIGURE 6-9 Basic machine-tool monitoring technique.

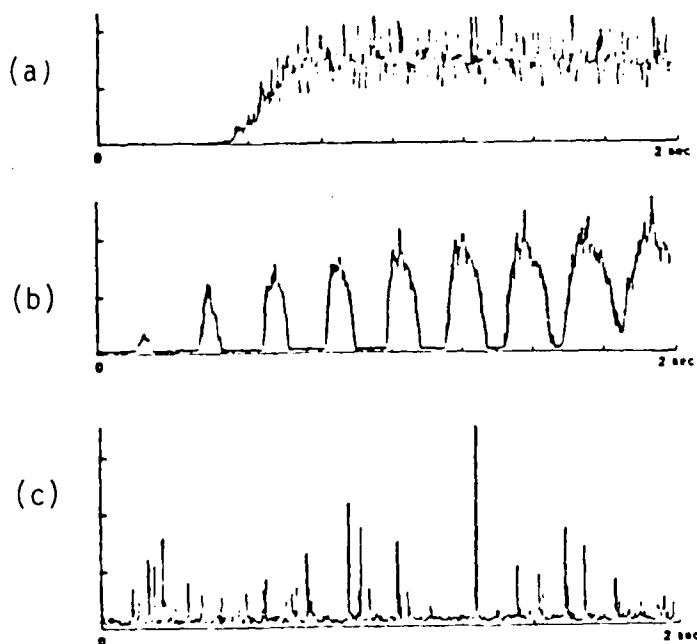


FIGURE 6-10 Three common normal cutting signal artifacts: (a) start of cut transient, (b) rough surface, intermittent cutting, and (c) chip dynamics noise.



Patterns applicable to tool breakage were then determined. As can be seen in Figure 6-11, these patterns, while not necessarily unique in instantaneous character, are unique in their persistence over an extended time increment of 1 to 2 seconds.

The tool breakage sensor based on accelerometric measurements was then developed. The accelerometer is affixed to the machine in a location that is acoustically coupled with the tool and calibrated to function within the expected operating limits. Its digital processor tracks the mean running condition within those limits and identifies tool breakage through recognition of abnormal operation for a defined period of time (e.g., 2 seconds).

Integration of this capability required a two-way communication interface with the numeric control. Parametric data are passed to the processor from the numerically controlled part program, and tool breakage events are signaled to special numeric control routines, which enact safe, automatic recovery routines.

The "touch" mode provides in-process inspection capability by acoustically detecting when the tool lightly touches or rubs the surface of a rotating part. Capturing the machine position where this touch occurs provides the basis for parts measurements. Similarly, if the touch is made on a known dimension (datum), the tool size can be determined. This approach has several advantages over touch-trigger probes. First,

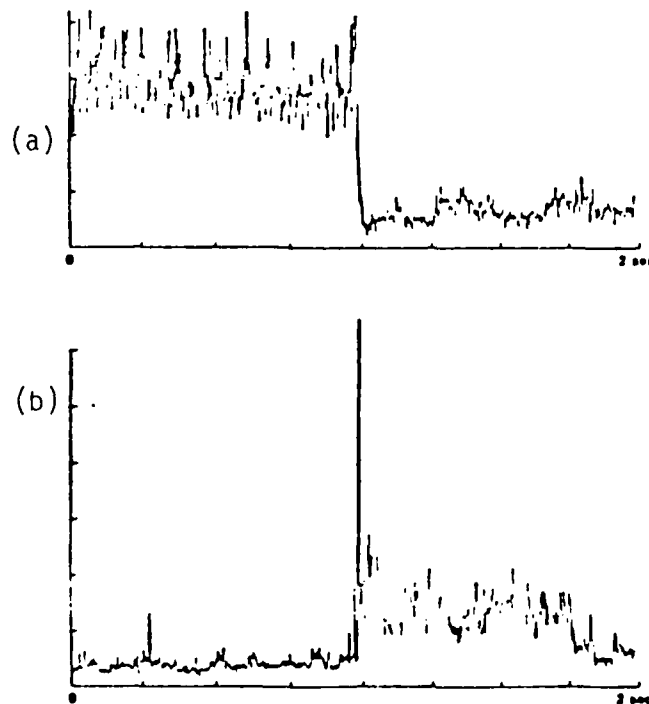


FIGURE 6-11 Two common types of tool break signatures: (a) abrupt, substantial, persistent level decrease and (b) abrupt, substantial, persistent level increase.

one sensor system accommodates both tool breakage and in-process inspection. Further, since the probe stylus is the machining tool being used, there is no susceptibility to stylus breakage. Likewise, accessibility to the part surface is not a problem.

This tool monitoring system is a key technology for reducing the human dependence in an automated machine cell.

### Data Bases

Another principal technical barrier with OLPC for metals processing is that of data bases, which for most cases do not exist in a complete or even a usable format. For the example of directional solidification, four categories of data base must be established: geometry, material, defect criteria, and knowledge.

Because of the nature of the capabilities of the investment casting, geometric complexity is essentially limitless and is taken to its full advantage with DS and SC turbine blade designs. This ultimately leads to the requirement of a rather extensive data base that fully describes the necessary features of the casting that will be needed in OLPC. Since the aircraft engine industry has a similar interest in using this geometry data base for design and manufacture of the engine, the task is to ensure that, in the design stage, sufficient data are produced to satisfy the needs of the investment foundries, that the format is usable, and that the pertinent data are easily retrievable.

In the area of material data bases, a wide variety of alloy chemistries and ceramic mold and core materials are used in the industry. Physical property data (i.e., thermal conductivity, specific heat, etc.) and thermal transport data (i.e., metal-mold gap resistance, emissivity, etc.) are needed. For most alloys these data exist at temperatures approaching the alloy melting point. Unfortunately, very little data exist in the two-phase liquid-solid region or liquid phase. Similarly, very little data exist for ceramic molds and cores. To further compound the situation, the empirical techniques to generate these data bases have not been totally agreed on or validated. The numerous alloys, ceramics, and empirical techniques result in a multitude of possibilities. Fortunately for the processing temperatures of interest, the required data show little scatter, thus simplifying the quantity of data necessary to develop statistical significance. Also, some of the necessary material data, such as thermal conductivity, seem to be alloy composition-insensitive, provided that the alloy is derived from a similar base element (e.g., nickel). Much work is needed to establish empirical techniques, uniform standard procedures, and actual data for the vast material data base.

In general, a defect criteria data base is seriously lacking. The interaction of processing parameters on defect formation may be understood in general terms but has not been quantified. For example, it is known that freckles may form if the solidification rate ( $R$ ) is too slow for a given thermal gradient ( $G$ ). This may be expressed in a simple  $G$  times  $R$  ( $GR$ ) term in which a certain minimum value must be exceeded. This minimum value is an alloy-sensitive constant, highly dependent on composition. This type of defect criterion needs to be defined for all defects (i.e.,

high-angle grain boundaries, slivers, equiaxed grains, etc.) for which some data exist to establish the mechanism of defect formation but little data exist to quantify the influence of process parameters.

The final data base need is the knowledge necessary to capture the years of process experience for implementation in expert systems. Knowledge acquisition is widely recognized as a major bottleneck in the development of practical (rather than simple prototype) expert systems. Even after the initial system is operational, the problem of knowledge acquisition remains severe, owing to the need for constant updating and extension of the knowledge bases. There is a need to identify experts and obtain the commitment to make them available "on demand" for the knowledge engineering team. This type of data base is new to most industries and requires a new discipline in documentation and interaction.

### Factory Hierarchies

For OLPC of metals processes, most systems envisioned for the next decade will probably be modular rather than entire plant installations. Examples of these modules (or cells), generally not fully automated, include continuous casting, specific ingot-to-billet conversion press facilities, and certain rolling-mill installations.

In the example of investment casting, the programmable robots commonly used for ceramic mold preparation or the programmable robots for automated gate removal are examples of islands of automation in an otherwise labor-intensive process. The need for ceramic mold integrity with thickness control and the removal of numerous complex gates for these often cumbersome, shaped, and heavy bodies make an ideal robotics application. Other manual operations such as mold knockout, cleaning, and inspection make it apparent that total CIC automation of the investment casting process will not occur in the near future. Within this decade, the factory hierarchies leading to OLPC of the investment casting process are perceived to improve quality and reliability.

The incremental implementation of OLPC technologies must also consider the ever-changing product requirements and vast variety of configurations. For example, one foundry may be producing up to 50 different part geometries out of 10 different alloy compositions in production. In addition, there may be an additional 10 different part geometries out of 5 different alloys under development. The sizes, shapes, requirements, and needs vary dramatically, making the need for OLPC flexibility mandatory.

### System Integration

The system integration required for OLPC begins with management and operator acceptance of change. Line management must accept loss of the direct control and decision-making functions built into the system and of their confidence placed in the equipment operators. The operators and their bargaining units must accept the work scope flexibility that accompanies OLPC. Issues such as multifunctional job codes and nontraditional work schedules must be accepted; otherwise, the cost benefits of OLPC systems will not be realized. There is little doubt that a national trend toward evaluating the product quality and cost benefits of OLPC has been

initiated. The question in reality is whether this casting market will be satisfied by existing producers, by new ventures in the United States, or by foreign producers.

The facilities support systems requirements, not yet ready for even pilot-plant study, are primarily sensors, data bases, and software programs. These needs are generally unique to specific facilities and therefore must be defined and developed in parallel with their intended application. For example, a sensor capable of detecting a liquid-solid interface through a ceramic mold of complex casting configuration, although ultimately of generic value, must first be developed by the initial practitioner. There is deserved concern regarding the cost and risk of developing such a sensor (or a workable alternative). Constructing an OLPC facility on the assumption that such a technology will exist when needed is obviously of even greater concern.

Software programs for OLPC facilities, while often costly, do not represent the risk level attributable to effective and durable sensor development. Software needs can be addressed in an evolutionary manner and modified as required for efficient facilities operation. The complexities of the control and integration of metals process variables, however, will require the development of expert systems.

The number of process variables to be monitored and considered in the control methodology may exceed human capacity to view, assess, and respond to in time to prevent process deviations. For these cases, algorithms generated by coupling of variables into the software are necessary. For example, it is envisioned that true OLPC of the SC investment casting process will monitor a variety of bulk parameters, such as temperatures of the mold, metal, and furnace, along with intrinsic characteristics of the resulting metallurgical structure, such as liquid-solid interface position and morphology. The abundant data must be received, interpreted, and utilized as input for further OLPC. A nontrivial task of OLPC is to plan for this multitude of data and to build-in the ability to choose pertinent data and ignore erroneous data, allowing the control scheme to perform effectively. As a further SC investment casting example, if sensor data obtained by monitoring the withdrawal cycle suggest that conditions are favorable for the formation of high-angle grain boundaries, other sensor data such as vacuum levels or furnace temperatures will take only secondary consideration in resolving the processing discrepancy. AI technology (expert systems) probably will be necessary for more effective and efficient control but at present is akin to an undeveloped sensor in terms of application risk.

### Economic Concerns

The startup of an OLPC facility often (if not always) entails higher initial costs. These startup costs are due to major factors attributable to most new process facilities:

- Return on investment, to include reasonable profitability and allowance for depreciation costs. These are fundamental to the willingness of any corporation to invest in plant modernization, for the purposes of this text, and need no further comment.

■ Unpredicted and unfavorable associated costs. These are usually attributable to such factors as low initial volume, unplanned technical problems, and certification barriers.

Unplanned technical problems can stalemate a well-founded analysis and, in fact, can even scuttle a major venture. Although this is perhaps inexcusable, it occurs far too often to be neglected. Stringent demands on equipment design and durability are necessary for problem avoidance. Generation of individual plant equipment and integrated systems reliability in actuality probably costs little more in time and resources than less well-planned ventures and should be part of the development rather than the post-production plan. The "build it now and fix it later" approach simply will not produce the desired systems capability.

A second form of technical failure can and does occur when new mousetrap A is inferior to new mousetrap B. It is most disconcerting to find too late that a competitive facility is superior to your most recent venture. Competitive intelligence plus willingness to assume reasonable risk, therefore, become serious considerations in facilities modernization. Again, this obvious pitfall too often leads to retrenchment or even abandonment of much-needed facilities modernization: "In the business versus not in the business."

Certification barriers, particularly in DOD systems approval, represent perhaps the largest obstacle to plant modernization. This is true because DOD product performance and reliability needs often outweigh the recognized objective of industrial modernization. These barriers take at least two major forms: (a) a structured procurement system that does not permit initial cost disadvantage for later cost superiority relative to proven state-of-the-art technology level; and (b) a product quality assurance plan that (often rightfully) imposes redundant and/or enhanced quality-assurance requirements on new or revised processes. These demands are often in opposition.

As pointed out previously, startup or learning-curve costs may have an adverse impact on the introduction of OLPC (or other) facilities. In today's DOD procurement world, the rules are proper and justifiable. Prime among these rules is that procurement awards are made to qualified sources based on cost (i.e., approved Foundry A has no advantage except cost over approved Foundry B or C regardless of its commitment or lack of commitment to facilities modernization). Although DOD technology funding such as "TechMod" or "ManTech" is often directed at offsetting this problem, it remains a significant barrier to plant modernization. True equity in commitment should instead be achieved by long-term specific cost agreements that permit startup costs to be deferred to later earned cost reduction. Although it is true that such agreements bind both parties in terms of market share and price, it is argued that real progress toward cost reduction requires the two-party dedication exemplified by this type of agreement. Table 6-1 gives a hypothetical example of such a scenario for investment casting. For the example of investment casting, it is shown that the startup cost of OLPC will undoubtedly exceed today's state-of-the-art process, primarily because of excessive debugging, depreciation, and direct manufacturing costs, although the maintenance

TABLE 6-1 Implementation Cost

Cost Item	<u>Implementation Cost (percent)</u>		
	Today's Process	Startup OLPC	Mature OLPC
Debugging	0	20	0
Depreciation	10	30	20
Maintenance	15	5	5
Idle time	20	0	10
Direct manufacturing	55	70	40
Total	100	125	75

and idle time may offset it to some degree. But what must be foreseen is the true cost benefit, which can be achieved as the OLPC matures. The majority of the savings comes from the reduced direct manufacturing cost and reduced maintenance.

The conflicting scenario of substantiated component quality prior to DOD (or prime contractor) new process acceptance can be cited in relationship to new parts (design) procurement. For new parts procurement, the cost associated with the technological benefit of the new part is, for the most part, included in the systems procurement contract defining product requirements. Therefore, for the advanced systems new parts case, the new process and/or material needs are factored into the systems mission payoff and development cost. For this reason, new processes are often introduced exclusively into new products--or not at all. In the case of a new process that offers an ultimate cost advantage over existing technology, no parallel development cost offset is allowed. The situation is worsened in that the cost of introduction frequently requires initial added product assurance cost. Table 6-2 considers this problem, using the same hypothetical new process used in Table 6-1.

The example for SC investment casting will illustrate the situation. The startup of OLPC will undoubtedly exceed that of today's state-of-the-art process. Virtually every operation will exhibit some degree of increased expense except inspection and repairs. But once the OLPC process matures, noticeable reduction in each operation, particularly the inspection and repair step, is anticipated, even though the actual cost to perform the highly monitored and controlled casting operation will be increased.

The bottom line of this example is that DOD recognition of new process start-up cost must accompany the recognized goal of industrial modernization. This conflict of purpose is particularly true when one considers modernization through OLPC.

TABLE 6-2 Relative Manufacturing Cost

Operation	Manufacturing Cost (percent)		
	Today's Process	Startup OLPC	Mature OLPC
Raw materials (alloy, cores, wax)	20	25	15
Precasting (pattern assembly, shell manufacturing, inspection)	15	25	10
Casting (mold preparation, casting)	10	30	20
Post-casting (knock-out, cleaning)	15	20	15
Inspection and repair (Zyglo, x-ray, benching)	40	30	10
Total	100	130	70

## SUMMARY

Aggressive programs are being undertaken to gain a better understanding of the solidification process (investment casting) through the implementation of computer-aided tools such as CAD, CAE, CAM, and ES. The use of these tools will determine sensitivity to casting integrity, along with identifying key casting parameters to monitor and identify critical sensor locations. Although this activity is anticipated to provide a significant advancement in the lead time, quality, and cost of new castings, much is yet to be accomplished to achieve consistency in the production of castings. Sensors, data bases, and system integration are definitely lagging behind and, for investment casting processes, are major technical obstacles to the implementation of OLPC. Furthermore, economic considerations of implementing OLPC may override technical barriers, requiring cooperative agreements between engine prime contractors, DOD, and casting vendors to achieve the full benefits of OLPC.

## REFERENCES

- Malas, J. 1986. A Thermodynamic and Continuum Approach to the Design and Control of Precision Forging Processes. M.S. Thesis, Wright State University, Dayton, Ohio.
- National Materials Advisory Board. 1986. Automated Nondestructive Characterization and Evaluation in Metal and Ceramic Powder Production. Report Numbers NMAB-442 and MTL TR 86-34 (Limited Distribution). Watertown, Massachusetts: Army Materials Technology Laboratory.

## Chapter 7

### FUTURE NEEDS AND BARRIERS

It is well recognized that, for U.S. manufacturing industries to be competitive, process automation and quality assurance based on on-line process controls must be implemented. In this study, the components of OLPC--process understanding, controls, and sensing--were examined and discussed in detail. Issues faced when implementing OLPC in metals processing have also been addressed. The committee's research, deliberations, and study point to the following needs:

- Much fundamental research is needed regarding process understanding and the development of relevant process models, particularly in processing far from equilibrium. In addition, fundamental research is needed in the simultaneous consideration of gradients in time with gradients in space.

- A new process design methodology needs to be developed that integrates fundamental understanding with numerical methods to simplify sensing and control. Such a methodology must clearly identify the relationship between control variables and performance margin and is needed to establish the control criteria for process selection. The process design methodology also needs to be constrained by a figure-of-merit approach to process durability.

- Process models will only bring forth process understanding if the developed models utilize accurate materials data. Unfortunately, the data base (e.g., viscosity, thermophysical properties as required in plasma processing, heat transfer coefficients as required in continuous casting processes) is nonexistent or not reliable. One suggestion is to initiate a cooperative joint industry-university-National Institute of Standards and Technology program funded by the federal government to measure and collect the required model parameters at industrial sites. Such data are extremely valuable and will have a significant impact.

- There is a need to improve the dialogue and technology transfer between the materials processing community and those involved in applicable measurement science. Consideration should be given to including sensor-related topics in the curricula of university materials science courses. The materials processing community has begun to explore consortia funding of specific sensor development efforts. These enable several companies to pool their resources and work collaboratively,



possibly with university and/or government research involvement. The advantage of this approach is that the risk:cost ratio is more acceptable for each participating company. Such efforts must be continued and supported.

- On-line connotes that the response is immediate. There are many metals processing operations where the computational time needed to be "on-line controlled" requires large computers. Here, the cost becomes prohibitive. Special-purpose computers designed for specific computational formalisms and enhanced speed are needed.

- Several metals processing centers at or near a university campus should be made available. The centers should "house" fellows from three or four different industries as well as university fellows (graduate students obtaining a degree in manufacturing science or materials processing and synthesis). Each of these centers should have a focus (e.g., advanced composite processing, near-net-shape manufacturing, casting, particulate processing). The mission of each center would be to develop the process models, the needed sensors, and the controls such that OLPC and process automation can be implemented.

- Basic research of generic aspects of sensor technology needs to be encouraged in industry, government, and universities. Sensors that measure the principal process variable(s) in real-time are essential and can significantly simplify the control task. Remote sensing capabilities need to be enhanced, new signal processing and analysis techniques await development, and sensor-media interaction modeling opportunities abound. Stronger federal support for these aspects of measurement science would do much to enhance the technology pool from which the materials processing community will draw its future sensor development efforts.

- A preferably verbal natural language interface for enhanced system input and output would revolutionize process control in industry. The primary constraint at the human interface level is expedient communication with the system, which would be facilitated by continuous speech recognition providing real-time processing of connected words. Speech synthesis is a less difficult (and less essential) process, but current methods require improved phonetics.

- A standard communication protocol between control hardware and data lines is required. In addition, the development of symbolic processing languages and methods that query faster should be expedited.

- Greater support of the cognitive sciences is considered to be necessary for the conceptualization of revolutionary computational devices. These advances can be in the area of information storage, processing speed, and system interfacing. It is expected that biochemical analogy (e.g., neuro-networks) has applications in rapid access, mass data storage, and hardware architecture.

The information that has been assembled by the committee and the recommendations that have been distilled from its deliberations will have no impact without a definite strategy for OLPC implementation. The committee recognizes the following obstacles:

- The lack of adequate sensors is an important impediment to the implementation of new materials processing strategies. The reasons appear to be as much institutional and organizational as fundamental limitations of measurement science. For example, the market for many specific sensors is small and fragmented, so it is difficult for a single company to show an acceptable return on investment in sensor research and development. Also, many of the sensor technologies of importance are only just emerging from research laboratories. Thus the technical expertise for sensor development often does not reside in either the research organizations of the materials processing community or the vendor companies supplying control instrumentation. Furthermore, those researchers who are conversant with emerging sensor technologies are often unaware of research opportunities in materials processing.

- The cost and risk barriers to the implementation of OLPC--particularly when coupled with a new materials technology such as high-temperature composites--are major obstacles. The potential investor is faced not only with the capital risk of successfully meeting the shop cost objectives of an OLPC venture but also with the risk of product need and/or acceptability, even if the plant product objectives are met. Close coordination among equipment manufacturer, product producer, and product user is a prime requirement. Beyond this, government stimulus (perhaps in the forms of prototype facilities subsidy, product evaluation support, and tolerance for the learning curve cost burden inherent in early production) may be necessary to establish initial capability, especially in cases where advanced processing concepts are combined with revolutionary materials compositions and forms.

- Product life cycles of more than 10 years are required to justify major plant expenditures.

- The materials data needed are costly to acquire.

- U.S. industry is investing in assembly plants in underdeveloped countries and is shipping production activities to these low-cost-labor locations. If this trend is not reversed, materials R&D will provide a base for competitors only and will cease to be supported in the United States.

The implementation of OLPC will require a strategic plan. U.S. industry needs to establish control of products and processes in current operations. Moreover, it needs to commit to long-term total integration of manufacturing systems.

## Appendix

### BIOGRAPHICAL SKETCHES OF COMMITTEE MEMBERS

**DIRAN APELIAN** is Howmet Professor of Materials Engineering, Director of the Solidification Processing Center, and Associate Dean of the College of Engineering at Drexel University. He received his B.S. degree from Drexel and his Sc.D. degree from Massachusetts Institute of Technology. Dr. Apelian worked at Bethlehem Steel Corporation before joining Drexel in 1976. He is a fellow of ASM International and a member of AAAS, AIME, AIChE, MRS, and the American Powder Metallurgy Institute. His principal research has been in various aspects of solidification processes.

**C. EDWARD ECKERT** received his B.S. and M.S. degrees from the University of Pittsburgh and is currently a Ph.D. candidate at Drexel University. In 1979, after 3 years at General Motors, Mr. Eckert joined Alcoa, where, as Sensor Technical Specialist, he conducts development of casting and purification processes. He is a member of TMS, ASM, and Sigma Xi.

**LIONEL C. KIMERLING** is head of the Materials Interface Research Department at AT&T Bell Laboratories, where he conducts an active research program in the structure, properties, and processing of semiconductor materials. He earned his bachelor's degree in metallurgical engineering and his doctorate in materials science at Massachusetts Institute of Technology. Prior to joining AT&T, he served in the U.S. Air Force at the Solid State Sciences Laboratory of the Air Force Cambridge Research Laboratories. He is the author of over 100 technical articles and sits on the editorial board of the Journal of Electronic Materials. He is a fellow of the American Physical Society; his other memberships include MRS, ECS, TMS, and AAAS.

**HARRIS MARCUS** is Harry L. Kent Professor of Mechanical Engineering and Director of the Center for Materials Science and Engineering at the University of Texas in Austin. He received his B.S. degree from Purdue University and his Ph.D. degree in materials science from Northwestern University. Prior to his association with the University of Texas he held positions at the Metals and Controls Division of Texas Instruments and at the Rockwell Science Center. His studies have included processing of materials, mechanical properties of materials, and applications of Auger and Mössbauer spectroscopy. Dr. Marcus is a member of TMS/AIME, ASM International, ASTM, ASME, MRS, and APS.

**DONALD R. SADOWAY** received his B.A.Sc., M.A.Sc. and Ph.D. (in metallurgy) from the University of Toronto. Dr. Sadoway has been on the faculty at Massachusetts Institute of Technology since 1978 and is currently Associate Professor of Materials Engineering. His work has concentrated on the electroprocessing of metals in molten salts. He is a member of TMS, AIME, ES, Canadian Institute of Mining and Metallurgy, International Society of Electrochemistry, and AAAS.

**ROBERT A. SPRAGUE** received his B.S.M.E from GMI Institute and his M.S. in metallurgy from Rennselaer Polytechnic Institute. Mr. Sprague has worked in the aircraft engine business for most of his career. After working for approximately 18 years at Pratt and Whitney Aircraft he moved to General Electric Company, where he is currently Division Staff Engineer in the Aircraft Engine Engineering Division. He is also Project General Manager for the Concurrent Engineering Program in the Engineering Division. He is a member of ASM International and AVS.

**HAYDN N. G. WADLEY** received his B.Sc. and Ph.D. degrees from the University of Reading in Great Britain. He is currently Professor of Materials Science and Mechanical/Aeronautical Engineering at the University of Virginia at Charlottesville. He was previously a Group Leader at the National Institute of Standards and Technology (formerly the National Bureau of Standards), where he had been since 1983. Earlier he was a senior scientist at AERE Harwell in Great Britain. His interests have been in aspects of nondestructive examination of materials. He is a member of MRS, APS, ASM International, and AIME.